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Data-drivenness: (big) data and data-driven enterprises

A multiple case study on B2B companies within the telecommunication sector

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Abstract

In the digitalization era where increasingly larger amount of data is created every day, companies have a great opportunity at their disposal: data-drivenness. It essentially implies that enterprises can exploit big data through Big Data Analytics (BDA) in order to gather relevant insights for their decisions.
However, the author realized the presence of little qualitative and scientific studies on data-drivenness as well as a major focus on US companies. Hence, this study aims at qualitatively exploring how enterprises are dealing with data-drivenness and how these are changing to become data-driven. It consists of a multiple case study on four Swedish-based B2B enterprises within the telecommunication sector. This choice seems to be intriguing for two main reasons. On one hand, B2C companies are often conceived as data-driven given their larger consumer base. But what about B2B ones? On the other hand, companies operating in the telecommunication sector are the building blocks of digital revolution that is the engine for the creation of data. But are they also exploiting data insights to run their businesses?

The findings from the study revealed that case companies are aware of what a data-driven enterprise is, and which are the elements characterizing it. First and foremost, big data and BDA are at the basis, not so much for the amount but for the ability of companies to combine various sources of data to generate actionable insights. However, data-drivenness results to be implemented at different degrees within case companies, mainly because of their different size and key characteristics. Moreover, for these having the target of full data-drivenness, some critical challenges preventing it are highlighted such as data quality issues, investments in human skills and technologies and the overall process of change. In particular, the last is undertaken by companies to become data-driven and respond to external influence and pressure from competition. In this regard, change entails tangible and intangible modifications that often encounter some resistance. De facto, it is plausible to believe that companies decide to start the journey toward data-drivenness in the light of opportunities connected to it such as the possibility of taking more accurate decisions (strategic and/or operational), finding innovation avenues and following market trends that might result in improving enterprise' competitive position. Finally, the research reveals that data-drivenness is a hot topic and the future prerequisite for companies to survive in an increasing digitalized and evolving world.

Keywords: digitalization; big data; big data analytics; data-drivenness; data-driven enterprise; data-driven company; organizational change.

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List of abbreviations

- FTK: First To Know Scandinavia
- B2C: Business To Consumers
- B2B: Business To Business
- BDA: Big Data Analytics
- IoT: Internet of Things
- AI: Artificial Intelligence
- HiPPO: Highest-paid person's opinion

1. Introduction

The purpose of this chapter is to introduce the topic and research questions of the thesis. Hence, the background and problem discussion are presented. Then, purpose and research questions are explained. Finally, the author provides a brief description of the sector chosen and of the examined companies to conclude with limitations of study and thesis' disposition.

1.1 Background

Nowadays, we are living in what can be defined as "digitalization era", where a vast number of technological innovations are being developed and made available to almost everyone (Pereira, et al., 2018). It is possible to consider digitalization as the surrounding in which companies are currently operating since it entails the application of digital technologies in many aspects of business (Parviainen, et al., 2017) . One of the main consequences of this shift toward a digitalized business environment is the creation of progressively larger amount of data that needs to be collected and handled (Pereira, et al., 2018), with big data analytics. Suffice it to say that in 2018 around 2.5 quintillion bytes of data were generated each day and that, impressively, 90% of todays' data has been created over the last two years (Marr, 2018).
Big data and BDA concepts have been addressed by many authors and a fairly complete explanation could be the one provided by Gartner IT Glossary defining big data is an asset characterized by high-volume, high-velocity and high-variety that requires efficient and new forms of information processing to provide insights and better decision making (Gartner IT Glossary, 2019 a).

In this context, it is plausible to believe that digitalization, big data and their analysis (BDA) act as an external pressure for companies that might need to adapt to these novelties to survive and remain competitive in the market. In fact, in order to stay competitive in the business environment companies are required to constantly adapt to changes (Boss, 2016) as the core of management is dealing with modifications in the external environment (Chakravarthy, 1982) such as technological developments. In particular, in the digitalization surrounding, the adoption of big data and BDA considered as new technologies, might enforce changes within organizations because their introduction requires new skillsets and adapted culture as well as top management support (Halaweh & Massry, 2015). Indeed, enterprises can exploit big data through its analysis in order to extract relevant insights, thus creating value (EY,2014). As a matter of fact, a key chance provided by big data and BDA is the possibility of guiding better decisions (Economist Intelligence Unit, 2012). The outcome is that many companies are considering and working for becoming data-driven considered as the winning bet for enterprises by Accenture Labs (2018). The concept "data-drivenness" could be gathered by the meaning of "drivenness" which refers to the quality of being guided (Collins English Dictionary, 2019) . Thus, it involves the idea of being driven by data. This concept has been addressed from different viewpoints and a common definition appears to be related to the ability of converting data into actionable insights and use it as piece of evidence to help and inform decisions (Anderson, 2015; Deloitte, 2016; Mikalef, et al., 2018; Accenture Labs, 2018).

Notwithistanding the opportunities associated with data-drivenness, many enterprises seem to experience various challenges in becoming data-driven. For instance, a research carried out by NewVantage Partners (2018) on the use that 60 leading companies among Fortune 1000 make of big data to become data-driven, points out that the main issues that prevents from its successful adoption are the cultural resistance and the difficulty related to adaptability to change. Moreover, a recent survey conducted over 64 c-level technology and business executives of US companies revealed that the majority of partipants have not yet embraced a data culture even if almost everyone admits the importance of big data and BDA for their organizations, also in terms of investments (Bean & Davenport, 2019). In this perspective, organizational change seems to be crucial.

1.2 Problem discussion

A preliminary analysis conducted by the researcher highlighted little qualitative and scientific studies on data-drivenness as well as a major focus on US companies in quantitative researches. For this reason, the author felt relevant and interesting to qualitatively study the topic, narrowing down the scope to Swedish-based enterprises, given the researcher geographical presence in Sweden. More in particular, the research focuses on B2B companies operating in the telecommunication sector and this choice seemed to be extremely intriguing for the following arguments. On one hand, it is often straightforward to believe that B2C companies are data-driven as they have the possibility to gather more insights thanks to a large consumer base. But what about B2B enterprises? On the other hand, companies operating in this sector are the building blocks for the digital revolution since they provide "access, interconnectivity and applications" and digitalization is the engine for the generation of increasing amount of data (Accenture Strategy, 2017). Thus, it appears interesting to explore how companies at the basis for the creation of big data are dealing with data-drivenness.

This study has been designed with the collaboration of First To Know Scandinavia AB (FTK), a Gothenburg-based consultancy company. In particular, with FTK the author selected the following Swedish companies to examine: TalkPool AB, Ericsson, GothNet and Telia Carrier.

1.3 Purpose and research questions

The purpose of this master thesis is to explore how B2B companies within the telecommunication sector, operating in the digitalization era, are dealing with big data and BDA in terms of becoming data-driven. In particular, the aim is to gather the similarities and differences among selected enterprises. Thus, to seek how they define data-drivenness, the main elements characterizing it, opportunities and challenges, their future expectations and the implied organizational changes if present. Hence, the main research question is construed as follows:

"How are B2B companies in the telecommunication sector dealing with data-drivenness?"

Moreover, since organizational change theories do not directly tie it to data-drivenness, the researcher decided to add a sub-question:

"How are these companies changing to become data-driven?"

Finally, the overall aim of this study is to provide a qualitative contribution to the existing studies around data-driven enterprises.

1.4 Telecommunication sector overview

Telecommunication sector comprises companies that enable communication on a global scale and it consists of three main sub-sectors: telecommunication equipment, telecom services and wireless telecommunication (Beers, 2019). More in detail, according to the classification provided by Dow Jones Industry, telecommunication services refer to "operating, maintaining or providing access to facilities for the transmission of voice, data, text and video between network termination points and telecommunications reselling" (Factiva, 2019 a). Based on the same source, telecommunication equipment entails "equipment and components used to enable the provision of telecommunications services". In this ample sector, 5G, IoT, optical fiber and cloud are considered as the main technologies now and for the next future (Rosmino, 2018).

Among the OECD countries, Sweden is at the forefront for telecommunication services and infrastructure and in 2016 the government published the Broadband Strategy with the goal of achieving "access to high-speed broadband in all of Sweden" by 2025 (OECD, 2018). In this perspective, Swedish companies operating in this sector are intensively working for 5G and IoT development (ibid.). Just to provide an example, Telia and Ericsson are partnering in order to create the first 5G network in Sweden (Davies, 2018).

1.5 Presentation of case companies

TalkPool AB

TalkPool AB is the Swedish company of TalkPool Group. Founded in Switzerland in 2000, TalkPool builds, maintains and improves networks worldwide (TalkPool, 2016). In 2014, TalkPool entered the Swedish market and the year after the legal entity TalkPool AB was founded, having as main focus the provision of IoT services. TalkPool AB is a fairly small company, with around 10-15 employees (de Bruin, B. & Lindgren, S., personal communication, 2019) while TalkPool Group consists of approximately 220 employees (TalkPool, 2016).

Ericsson

Established in Sweden in 1876, Ericsson is a worldwide provider of telecommunications equipment and related services to fixed and mobile network operators (Factiva, 2019 b). The global headquarter is in Stockholm and it is listed both on Nasdaq Stockholm and NASDAQ in New York (Ericsson, 2019 a). In Sweden, Ericsson consists of around 12.000 employees of a total workforce of more than 100.000 people and it covers all business areas such as sales, production, administration and R&D (ibid.). Ericsson portfolio includes four areas named Networks, Digital Services, Managed Services, and Emerging Business and in Sweden the main effort is put on 5G development (ibid.).

GothNet

Goteborg Energi GothNet AB (shortly called GothNet) is a fully owned subsidiary of the Swedish municipal company Goteborg Energi, established more than 150 years ago in the homonymous city (Goteborg Energi, 2019). GothNet was founded in 2000 and it consists of about 40 people (Hartmann, M., personal communication, 2019). The company owns and operates urban network with fiber networks, thus providing telecommunication services to telecom operators, public enterprises, companies and property owners within Gothenburg and Vastra Gotaland areas (ibid.).

Telia Carrier

Founded in 1991 in Sweden and fully owned by Telia Company, Telia Carrier provides various telecommunications services internationally (Telia Carrier, 2019). The enterprise consists of around 450 employees (Telia Company, 2018), that cannot be counted per country given the absence of geographical divisions. The services provided pertains to connectivity, transport, roaming, voice, network outsourcing and infrastructure (Telia Carrier, 2019). Moreover, Telia Carrier’s fiber backbone runs in 35 countries around the world (Telia Company, 2019).

1.6 Limitations

The limitations of this study mainly range along two dimensions: time availability and researcher's background.

On one hand, due to time limitations a small number of companies has been selected to be part of the research. Moreover, despite the fact that for bigger companies interviewing more representatives would have led to an even deeper exploration of the topic, it was not feasible to interview more than the ones reported in tables of respondents (paragraph 3.3). Anyway, for the scope of the research the author judged the data collected exhaustive and complete to draw conclusions. Furthermore, as anticipated in the problem discussion (paragraph 1.2), given the researcher geographical presence in Sweden and the limited time available to conduct the study, the analyzed companies are Swedish-based.

On the other hand, the researcher background resulted in the necessity of conducting the study from a business and managerial perspectives where technical aspects of the analyzed topic have not been deepened. Although, according to the researcher this does not undermine the value of the study.

1.7 Thesis disposition

Table 1: Thesis disposition

1.Introduction: presentation of background and problem discussion, purpose and research questions, telecommunication sector overview, case companies presentation and limitations discussion
2.Literature review: portrayal of theory on digitalization, big data and big data analytics, data-drivenness and organizational change
3.Methodology: explanation of research strategy and design, research method and data collection, data analysis and research quality
4.Data collection: outline of data collected with interviews from experts and case companies
5.Data analysis: analysis of empirical findings
6.Conclusions: presentation of conclusions and answers to RQs, outline of some final remarks about case companies and future research proposals

2. Literature review

This chapter presents the theoretical background that this thesis is based on. Digitalization is presented as the surrounding environment in which companies operate nowadays. Then, theory on big data and big data analytics is discussed since these are drivers and consequences of digitalization as well as at the foundation of data-drivenness. Thus, data-drivenness is presented highlighting its main features, opportunities and challenges. Finally, theory on organizational change is provided.

2.1 Digitalization

The 21st century is increasingly being characterized by a digital nature (Pereira, et al., 2018). From a wide viewpoint, digital economy is the "application of internet-based technologies for the production and trade of goods and services" (UNCTAD, 2017). The digital essence is clearly shown by the number of technological innovations that are being developed nowadays and that are made available to almost everyone (Pereira, et al., 2018). This phenomenon is usually described using the terms digitalization and digital transformation. In general terms, digital transformation is defined as the set of changes which are provoked by digital technology in different aspects of human life (Stolterman & Croon Fors, 2004).

In the context of this study, digitalization and digital transformation are analyzed from companies' angle since they are considered by the author as phenomena surrounding the business environment.

Digitalization and digital transformation are regarded as almost synonymous as they entail a fundamental change for organizations facing them (Parviainen, et al., 2017). Moreover, according to Pasini and Perego (2016) these words do not have a unique meaning or definition as they can be conceived as an "umbrella" enclosing several digital technologies, relevant for the functioning of firms and markets (Pasini & Perego , 2016). Notwithstanding the fact that a single definition does not exist, some interpretations of this concept are presented, since they seem to be relevant to provide a proper background to this study.

Digitalization is associated with the introduction or wider use of digital technologies by an organization or industry (Parviainen, et al., 2017). It is currently hitting almost every business and many companies are experiencing a transition process (Andersson & Rosenqvist, 2018). Similarly, Parviainen, et al. (2017) believe that digital transformation implicates modifications in the way of managing the business caused by the application of digital technologies. These changes might happen at different levels of the organization, namely process, organization and business domain (ibid.). Briefly, at a process level, digital means are used to partially substitute manual work; at an organization level modification involve the offer of new services or former services in a different manner; at a business domain level roles and value chains are reshaped.

When considering a groundbreaking phenomenon as this, both benefits and challenges for companies should be analyzed. Before presenting them, it is essential to point out that, the list that will be presented is non-exhaustive since they may vary across sectors and the enterprise perspective is taken. On one hand, as far as the benefits are concerned, a research conducted by the consultancy firm McKinsey states that if companies react aggressively to digitalization, their projected revenues and profits are likely to grow (Bughin, et al., 2017). From the other side of the coin, thanks to the adoption of digital technologies companies might cut costs up to 90% (Parviainen, et al., 2017). Furthermore, by automating processes these might turn to be more efficient (Fitzgerald , et al., 2013) and the collection of real time data may provide improved control on process performance and problem management (Parviainen, et al., 2017).
On the other hand, with regards to challenges faced by companies when tackling the digital transformation, some concern technological aspect while others managerial aspect. In particular, the lack of experience to drive transformation through technology and the requirement of building platforms and big data management are part of the first aspect (Fitzgerald , et al., 2013; Andersson & Rosenqvist, 2018). The managerial aspect concerns the necessity of changing organizations' modus operandi and business models due to higher cooperation and increased importance of service-based offerings (Parviainen, et al., 2017; Andersson & Rosenqvist, 2018).

Given the definitions provided above, it is noticeable that digital technologies play a central role in characterizing digitalization. Hence, it appears indispensable to give a general overview of what is intended by that expression. Based on a research conducted by the General Confederation of Italian Industry and the Italian Association for Information Technology, the main technological drivers are business intelligence and big data, cloud, Internet of Things (IoT), information security, advanced machine learning and collaborative robotics (Assinform, 2016). Similarly, according to a book focused on the drivers of digital transformation, the main ones are the mobile technologies, analytics, cloud computing and IoT (Chalons & Dufft, 2017).

For the purpose of this thesis, it does not seem significant to detailly define each technological innovation mentioned in the previous paragraph. Therefore, the one the researcher will focus on in the next section is big data and related analytics. In fact, data are not only drivers but also consequences of the gradual switch toward a digitalized business environment, where progressively larger amount of it is created, collected and managed (Pereira, et al., 2018).

2.2 Big Data and Big Data Analytics

Given that big data and BDA are considered at the foundation of data-drivenness, as explained in 2.3, the researcher decided to dedicate a separate paragraph to them. As a matter of fact, these concepts constitute the basics to understand what will be covered later on along the research.

2.2.1 Defining Big Data

Big data is an emphasized topic in information system, management and social science research (Constantiou & Kallinikos, 2015). As reported by Haider and Gandomi (2015), the term took over around 10 years ago, probably as a consequence of the development and promotion of the analytics market by leading technology companies such as IBM (Haider & Gandomi, 2015). However, despite the fact that this concept is largely discussed among researchers and practitioners, high level of vagueness about its meaning is still present (Hartmann, et al., 2014). For instance, while some researchers associate “big data” to the volume aspect, others consider it as a technology used by companies to analyze large amounts of information (Halaweh & Massry, 2015). Similarly, from firms’ perspectives, big data might be associated with different aspects depending on their activity (Blackburn, et al., 2017). In particular, for those usually handling enormous sets of data, it might entail the use of highly innovative data management technologies (ibid.). Conversely, for other organizations it might refers to data that cannot be processed solely using Microsoft Excel (ibid.).

Due to the confusion around big data definitions and for the purpose of providing a proper background on this, the author decided to start from a systematic review that presents several explanations that have been associated with big data along time (Mikalef, et al., 2018). Back in 2011, big data has been defined as involving the storage, management, analysis and representation of big and intricated datasets (Russom, 2011). Likewise, resting on Russom’s definition, Bekmamedova and Shanks (2014) state that it requires new data-management tools for processing higher volumes of data from social media (Bekmamedova & Shanks, 2014). In the same line, the year before, Bharadwaj, et al. (2013) point out that big data involves data whose volume is much higher than the ability of common processing devices of collecting and handling the data (Bharadwaj, et al., 2013).

Differently, other explanations concentrate less on the technical aspect and mainly focus on the dimensional features of big data. According to McAffe et al. (2012) velocity, volume and variety are the elements that distinguish big data from traditional analytics. Schroeck, et al. (2012) define big data as the union of volume, variety, velocity and veracity that provides companies the possibility to

obtain a competitive advantage (Schroeck, et al., 2012). Correspondingly, "big data consists of expansive collections of data (large volumes) that are updated quickly and frequently (high velocity) and that exhibit a huge range of different formats and content (wide variety)" (Davis, 2014 p.41). Two years later, other authors define big data using the same dimensions as Davis (2014) plus veracity (Akter, et al., 2016; Abbasi, et al., 2016).
Furthermore, in line with previous academic definitions, Gartner IT Glossary states that big data is an asset characterized by high-volume, high-velocity and high-variety that requires efficient and new forms of information processing to provide insights and better decision making (Gartner IT Glossary, 2019 a) whereas the TechAmerica Foundation's Federal Big Data Commission defines big data as a word describing "large volumes of high velocity, complex and variable data" that needs advanced analytics tools (TechAmerica Foundation's Federal Big Data Commission, 2012).

As it is deteactable from the overview on the definitions displayed above, two common factors among them are the dimensional aspect of big data and the technical aspect of big data analytics. For this reason, the next two paragraphs will provide the reader knowledge about these topics.

2.2.2 Big Data dimensions

Before presenting the dimensions qualifying big data, it is significant to clarify that it is not plausible to measure them according to universal thresholds given that they vary across size, sector and location of enterprises (Haider & Gandomi, 2015). Moreover, limits are likely to change over time as technologies for storing, managing and analyzing data evolve (ibid.).
Among the dimensions attributed to big data, three of them, known as 3Vs, are the most recurring: volume, variety and velocity.

Volume is described as the amount of data that is collected and/or generated by individuals or organizations (Lee, 2017), hence it is the size of data (Haider & Gandomi, 2015). Furthermore, volume depicts the (big) size of a dataset caused by the aggregation of large number of variables and large set of observations of each variable (George, et al., 2016).

Variety refers to the diversity in a set of data (Haider & Gandomi, 2015) and it is generated by the heterogeneity found in the types of data (George, et al., 2016). In fact, data can be categorized into three main species that range along a continuum: (1) structured, (2) unstructured and (3) semi-structured. The first type concerns data that can be collected and systematized in relational databases or spreadsheets such as sales transactions (Halaweh & Massry, 2015). The second typology entails data that are organized without a pre-defined model (ibid.) and that often do not have the structural organization necessary for analysis with machines (Haider & Gandomi, 2015). Moreover, this type of source is the one that mainly distinguish big data from traditional data set. Examples of this category are text, images, audio and video. Finally, semi-structured data places in between the previously explained categories, since it does not correspond to exact specifications (ibid.).

Velocity is defined as the pace at which data is created and analyzed (Lee, 2017) or as the speed at which data is generated and the rate at which it should be processed by organizations (Haider & Gandomi, 2015). Furthermore, Lee (2017) specifies that this dimension of data has grown over time and currently it can be said that it has a real-time pace.

Beyond the traditional dimensions presented above, big data has been associated with mainly other four characteristics that will be explained now and that constitute the 7Vs dimension model.

Veracity is a feature that, based on the research of Haider and Gandomi (2015), is added by IBM, referring to the lack of reliability of some sources of data. To provide an example, the sentimental aspect that people manifest on social media involves data that is, to some extent, untrustworthy since it implicates human judgment. In a more detailed manner, veracity can be addressed considering two factors (Demchenko, et al., 2013). On one hand, data consistency is measured with statistical reliability. On the other hand, data trustworthiness is assessed evaluating many factors such as data origin and methods of collection with reliable tools. Hence, veracity guarantees that data is reliable and prevented from illegitimate access and modifications (ibid.).

Variability is coined by SAS[1] to describe the variation in the velocity rate of data, caused by periodic ups and downs (Haider & Gandomi, 2015). SAS connects variability with complexity arising from the presence of too many sources of data generation (ibid.). In a different manner variability is also addressed by Seddom and Currie (2017) who refers to the powerful opportunities that become available by interpreting data (Seddon & Currie, 2017).

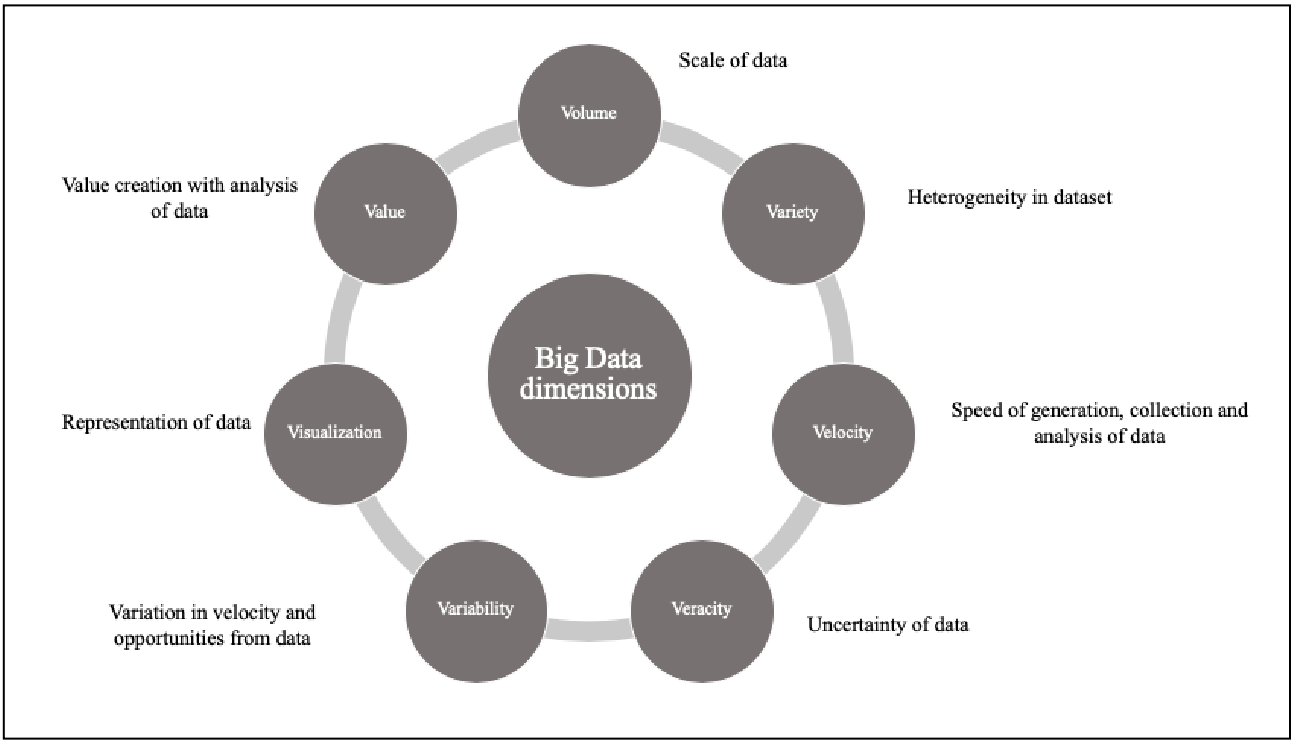
Value is introduced by Oracle to explain that data are characterized by "low value density" meaning that at the moment of collection it has low value compared to volume, but value is likely to increase after a proper analysis (Haider & Gandomi, 2015). Similarly, value is defined as the ability of big

[1] https://www.sas.com/en_nz/company-information/profile.html

data of providing helpful insights and opportunities for businesses thanks to extraction and processing (Wamba, et al., 2015).

Finally, visualization is employed by Seddon and Currie (2017) to elucidate the generation of models to represent data by using technologies such as artificial intelligence (AI). Data visualization is the graphical representation of data and when it comes to big and real-time data, it can become a complex activity (Gorodov & Gubarev, 2013). Thus, many different techniques have been developed (ibid.) and AI helps in this since it is described as the application of "advanced analytics and logic-based techniques, including machine learning, to interpret events, support and automate decisions, and take actions" (Gartner IT Glossary, 2019 b).

Figure 1: Big Data dimensions



(source: own elaboration)

2.2.3 Big Data Analytics

BDA is associated with the technical or technological aspect of big data since, in order to extract value from it, organizations need to process and analyze data (EY,2014). In reality, the ideas behind it are not novel because businesses have been dealing with data analysis for many years, by using Business Intelligence tools (Ohlhorst, 2013). Thus, BDA can be considered as an evolution of Business Intelligence and Business Analytics which became widespread around 1990s-2000s (Chen, et al., 2012). In the following years, the term big data analytics was coined as a consequence of the digitalization phenomenon that contributed to the creation of massive and diverse amounts of data (ibid.).

Indeed, in accordance with the explanation provided by Chen, et al. (2012), BDA refers to analytical techniques necessary to handle large, complex and mainly unstructured datasets. The aim of BDA is to extract value and insights from raw data (Blackburn, et al., 2017) as well as intelligence (Haider & Gandomi, 2015). Currently, there are many different BDA techniques such as text analytics, audio and video analytics but the detailed explanation of each is beyond the scope of this thesis. Conversely, what seems to be relevant in the light of what will be discussed later on, is presenting a brief taxonomy of three types of analytics: descriptive, predictive and prescriptive (Blackburn, et al., 2017). In fact, information revealed through BDA range along different time periods and this constitutes the basis for their distinction. In particular, descriptive analytics enables to detect what has happened in the past or what is happening in the present; predictive analytics allows to make forecasts and estimations for the future; prescriptive analytics suggests what one should do with respect to different options available (ibid.).

2.2.4 Big Data value chain

Commonly, the value chain is a framework used to represent the value-adding activities of an organization. In this context, the value chain can be applied to understand the process of value creation of data and it can be defined "Data Value Chain" (Curry, 2016). Considering big data as raw material (Chen, et al., 2014), information flow is depicted by Curry (2016) as the set of steps through which companies can gather insights from data and create value. The main steps of this value chain can be grouped as: data generation and acquisition; data analysis; data curation; data storage and data usage. These will be briefly presented below.

Data generation and acquisition

As presented in paragraph 2.2.2 (Big Data dimensions), one key characteristic defining big data is the variety of sources information

comes from. The first basic distinction concerning structured, unstructured and semi-structured data has been already explained in 2.2.2. In addition to that, given that business activities are progressively more digitized and that "each of us is now a walking data generator" (McAffe et al., 2012), it seems relevant to describe their origin.

In general terms, the key facilitators for the creation of increasingly larger amount of data are: (1) increase in storage capabilities, (2) increase in processing power and (3) availability of data (Mohan, 2016). As a matter of fact, on one hand more data is produced since individuals and organizations are always more interconnected. On the other, the increase in storage capabilities and processing power enables the extraction of valuable insights for companies that facilitate the creation of more customer-tight offers. This in turn gives the chance to attract more customers that will generate more data and so on. This loop is defined “data-network effect” by the Economist (The Economist , 2017).

In a more detailed manner, Ghotkar and Rokde (2016) and Chen, et al. (2014) present three main sources of big data that are explained below.

Firstly, industry machineries and vehicles generate data through real-time sensors (Ghotkar & Rokde, 2016), that are connected to each other with Internet of Things (IoT) (Chen, et al., 2014). IoT is defined as a network of physical devices embedding software, electronics and sensors that enable the exchange of data among devices (Kundhavai & Sridevi , 2016). To provide a comprehensive view to the reader it is important to say that, according to Kundhavai and Sridevi (2016), IoT is not only the enabler but also the result of big data because it uses analytics that improve processes for more IoT devices.

Secondly, information is created by human interactions through social media and blogging sites such as status update, picture posting (Ghotkar & Rokde, 2016; Chen, et al., 2014). Therefore, the human generated data is mainly unstructured.

Thirdly, a vast component of source is provided by data generated within enterprises (internal data) that is principally structured, such as operation and trading information (Ghotkar & Rokde, 2016; Chen, et al., 2014).

From a different angle, Sathi (2012) identifies other three drivers of big data, namely sophisticated customers, automation and monetization (Sathi, 2012). The first refers to the characteristic of customers that are more and more connected and use social media to gather real-time opinions from others. The second concerns the digital means which allow to capture massive amounts of data for analysis. The last entails the creation of an external market place where organizations exchange and trade customers’ information.

Once that data has been generated, organizations collect and might acquire it with the objective of including data in their value creation. The acquisition of data is described as the collection and the cleansing of data before storing it (Curry, 2016), using a proper transmission mechanism (Chen, et al., 2014).

Big Data analysis

Big data analysis has been partly described in previous paragraph (2.2.3) since it is a key technical aspect to consider when dealing with big data. Nevertheless, when describing the data value-chain, Curry (2016) suggests that big data analysis is the step during which organizations explore, transform and model data with the goal of finding out the most important information for their purposes.

Big Data curation

This step includes all the activities of data management suitable for ensuring that data quality standards are met (Curry, 2016). Of course, quality requirements vary across companies but, generally speaking, one can say that they ensure that data is reliable, accessible and usable (ibid). Curry and Freitas (2016) point out that this phase of the value chain has become essential as a consequence of the increase in the number of sources of big data creation (Curry & Freitas, 2016).

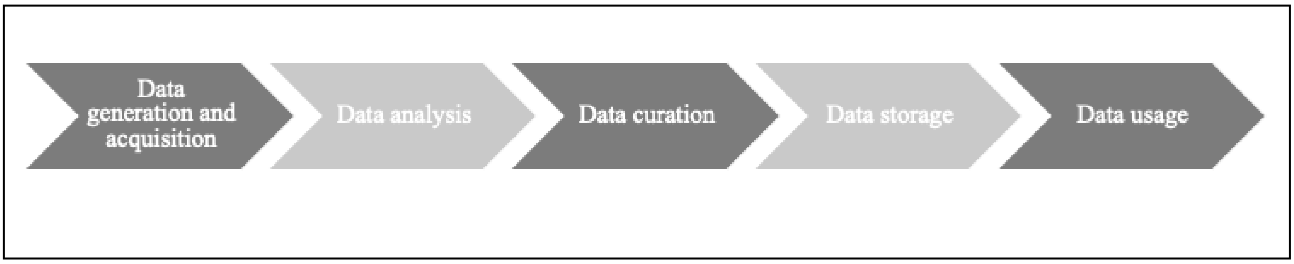
Big Data storage

This phase is associated with the storage and management of datasets in a way that permits a fast access to data (Curry, 2016). Traditionally, the storage has been carried out with Relational Database Management Systems (RDBMS). However, as anticipated while describing structured data in paragraph 2.2.2, these are less used to deal with unstructured data since they lack flexibility (Curry, 2016). Therefore, NoSQL databases have been invented to deal with big data.
Since this study follows a business perspective and not an engineering one, a deeper explanation of these storage systems will not be provided.

Big Data usage

The data value-chain finishes with the data usage which entails tools and activities necessary to integrate data within business decisions (Curry, 2016). This step is also defined by Miller and Mork (2013) as data exploitation to describe the phase in which the company uses previously analyzed data to take informed decisions (Miller & Mork, 2013).

Figure 2: Big Data value chain



(source: own elaboration from Curry (2016))

2.2.5 Opportunities and challenges of Big Data and Big Data Analytics

When it comes to big data and their analysis, organizations face both opportunities and challenges. These might vary across industries, sectors and specific companies' activities, for instance healthcare and transport sectors face different opportunities and challenges which are related to their specific contexts. Hence, since case companies in this study perform different activities, the author will provide an overview of opportunities and challenges which apply to various contexts.

2.2.5.1 Opportunities

Generally speaking, and from the point of view of a consultancy firm (EY,2014), these companies that invest in big data and that are capable of capturing valuable insights from it, are likely to obtain an advantage over competitors. That might be because of mainly three widely accepted opportunities coming from big data and BDA.

Firstly, they enable to identify and discover unknown paths that otherwise would have not been disclosed and to follow and catch simpler the arising market trends (Halaweh & Massry, 2015). That is related to both the possibility of creating new businesses, products and services (Lee, 2017) and to the chance of improving the innovation process of R&D (Blackburn, et al., 2017).

Secondly, by applying more automation with BDA companies can streamline their operations and improve business processes, resulting in operational cost reductions (Lee, 2017; Halaweh & Massry, 2015).

Thirdly, but not for importance order, managers have incredibly more information about their businesses than before and they can potentially transfer this knowledge to better decision making and improved performance (McAfee & Brynjolfsson, 2012; Brynjolfsson, 2012). Indeed, the potential value of big data is unlatched thanks to the capability of guiding better decisions (Economist Intelligence Unit, 2012), hence when it is "leveraged to drive decision making" (Haider & Gandomi, 2015, p. 140).

The idea behind the last opportunity presented will be further addressed later on (section 2.3) since data-driven decision making is at the core of the data-drivenness concept.

2.2.5.2 Challenges

Sivarajah, et al. (2017) divide big data challenges in three main categories, namely data challenges, process challenge and management challenge (Sivarajah, et al., 2017).

Data challenges pertain to the features of data itself. In particular, veracity and complexity are the two main characteristics that are likely to pose major concerns. In fact, organizations need to make sure that sources of data are reliable before using them while, at the same time, combine and transform huge amount of data coming from different and several sources (Haider & Gandomi, 2015).

Process challenges concern the processing of data along the value chain. In fact, Halaweh and Massry (2015) argue that companies willing to embrace big data and BDA, might face challenges in implementing them given the need of skillset. Indeed, they point out that new jobs need to be created as a consequence of big data, such as data scientist and data analyst (Halaweh & Massry, 2015).

Management challenges refer to both privacy and managerial viewpoint issues. As far as the former, much information is collected from individuals unbeknown to them, thus for organizations it is difficult to maintain acceptable privacy level and security control (Halaweh & Massry, 2015). The latter concerns what McAfee and Brynjolfsson (2012) name five management challenges, faced by companies while managing the change. The first is leadership since organizations embracing big data and BDA need to have "leadership teams" who set objectives and understand how to use insights obtained through data analysis. The second is called talent management and can be viewed as a consequence of the process challenge expressed by Halaweh and Massry (2015). In fact, companies need to hire data and computer scientists and they should be capable of actively interact with leaders and executives to help them in understanding how to formulate issues in a way that big data can tackle. The third challenge concerns the technology, meaning that it becomes a management issues since it should be part of a big data strategy. The fourth challenge is the downside of one of the opportunities presented above: decision-making. In fact, companies face the challenge of establishing cross-functional cooperation between "people who understand the problems" and those capable of exploit the data to solve them. The last challenge presented concerns the broad topic of company culture and companies might face it when they are willing to become data-driven organizations.

As anticipated above, McAfee and Brynjolfsson (2012) indicate that embracing big data and BDA poses the need to change. In the same line of argument, Halaweh and Massry (2015) present organizational change as one important challenge faced by organizations if considering big data and BDA as introduction of new technology/innovation. In fact, in this circumstance, it requires skillset and culture and top management support (ibid.)

Hence, since organizational change and adaptation seem to be essentials for companies in big data era, these will be the focus of a later paragraph of this study (2.4).

2.3 Data-drivenness

2.3.1 Defining data-drivenness

As anticipated in the paragraph presenting the opportunities arising from big data and big data analytics (2.2.5.1) one key chance relates to the possibility of enhancing decision-making process. These companies that are able to convert big data into actionable insights and use it as important piece of evidence to help and inform decisions are defined as "data-driven" (Anderson, 2015). According to Anderson (2015), a practitioner who wrote a book on this topic, being data-driven does not mean that a company entitles data to do and decide everything, but rather that the evidence from data coupled with the background and expertise of decision makers drives the decisions.

Similarly, according to the consultancy firm Accenture, an enterprise is data-driven when it considers data at the foundation of business decision-making by applying high quality analytics (Accenture Labs, 2018). Furthermore, by using the definition "insight-driven organization", another consultancy firm, describes a company that embeds data, insights and understanding into the decision-making process (Deloitte, 2016). In addition, Mikalef, et al. (2018) presents the concept of "BDA capability" that is defined by several scholars as the competence of a company to supply insight and understanding by utilizing data management, data infrastructure and skills that enable to obtain a competitive advantage. In this path, the term is used to consider big data as an expanded topic comprising all organizational resources needed to create capabilities enhancing the exploitation of big data at full potential (Mikalef, et al., 2018). This is similar to what Anderson (2015) names using the term "data-drivenness". Shortly, it can be described as the capacity of "bulding tools, abilities and a culture that acts on data" (Anderson, 2015, p.1).

Thus, in order to appreciate the full potential of big data and BDA in driving decisions, it is important to explain what "data-drivenness" comprises. Literally speaking, "drivenness" refers to the quality of being guided (Collins English Dictionary, 2019), thus "data-drivenness" involves the action of being driven by data.

Notwithstanding the way of calling this concept and with the aim of providing a proper background on this topic, the researcher will present below some elements characterizing data-drivenness. These have been identified through an extensive research conducted by the author given that a unique academic framework apt to explain data-drivenness seems not to have been developed, yet.

2.3.1.1 Data-drivenness elements

Tangible resources

Without data, a data-driven enterprise is not even imaginable, so the prerequisite is to have data, that is the tangible resource at the foundation of such organization (Mikalef, et al., 2018). Collecting data is not enough because companies need the right data to base their decisions on (Wessel, 2016). It means that it is often preferable to have a smaller amount of relevant data rather than amounts of unuseful information (Anderson, 2015). Thus, to be at the core, data must be appropriate, accurate, well-organized, well-documented and uniformely formatted (Patil & Mason, 2015). Another element that can be consider vital, is the infrastructure to collect and handle data (Mikalef, et al., 2018). In fact, as explained during the presentation of the big data value chain (section 2.2.4), data is just a raw material that needs to be analyzed to provide useful insights. However, collection and analysis of data are not sufficient if it is unaccessible from people in the organization (Anderson, 2015). In fact, data should be shareable and questionable across the enterprise and this is often referred to "democratization of data" (Patil & Mason, 2015). This concept refers to the ability of everyone in the company to access data in the limits of the legality (ibid). To strenghten this idea, they provide the example of Facebook that was the first to offer their employees the possibility to access data with the underling idea that wihtout it, poor business decisions were taken (ibid.). In a similar line of argument, Scott (2018) highlights the negative effect provoked when data are available only in silos, preventing companies from having an overall picture (Scott, 2018).

Intangible resources

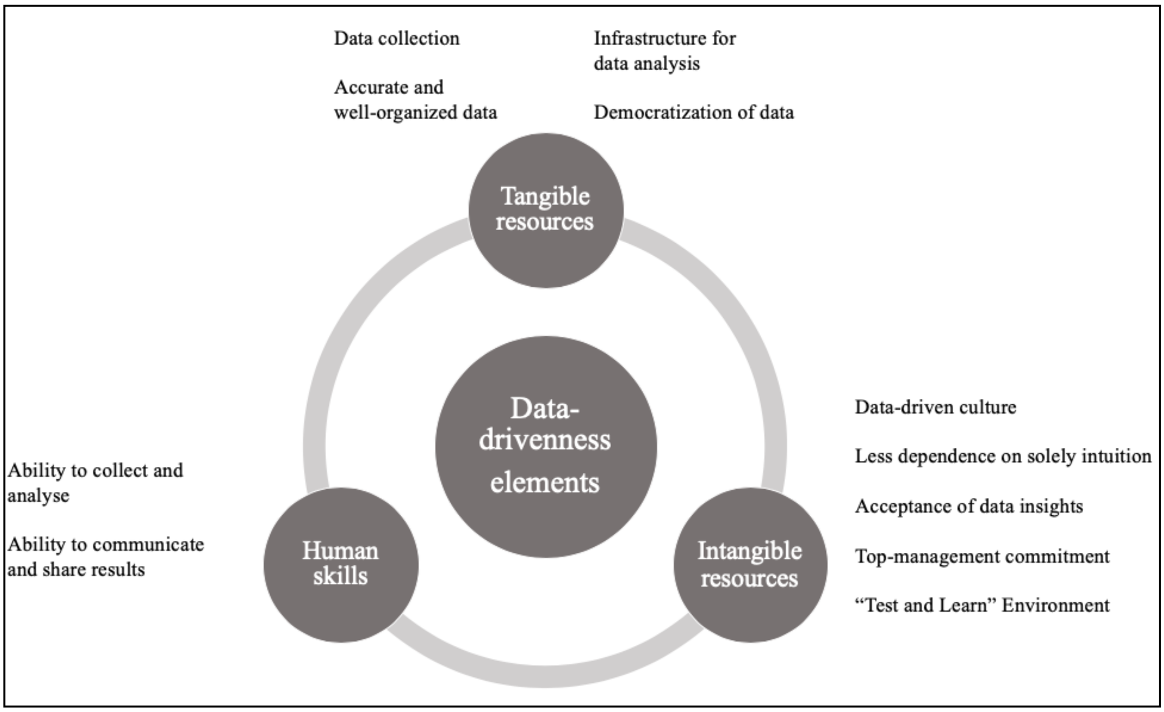
Intangible resources are defined as "ties, structures and roles established to manage the different types of resources" (Mikalef, et al., 2018, p.14). In data-drivenness, the main intangible resource relates to data-driven culture (Anderson, 2015; Mikalef, et al., 2018). In general, organizational culture defines the mindset and the way in which people within it act and take decisions (Jones, 2013a). It is a broad and complicated topic which suggests the importance of having a shared vision, realized through specific practices, on the use of data to drive decisions at different levels of the organization (Deloitte, 2016). In this line of argument, according to Anderson (2015), the fact that organizations take data-based decisions to a greater extent, can be viewed as the result of their culture that establishes the mentality and the process through which they can observe data, count on it and be influenced. Establishing data-driven culture entails the top management commitment to BDA and its ability to use it to make decision (Mikalef, et al., 2017). Trieu, et al. (2018) describes the mindset as a "fact-based decision-making culture" indicating that it requires decision-makers to be inclined to accept data-driven insights. In this line of argument, according to McAfee and Brynjolfsson (2012) the first element characterizing data-driven culture is the reduction of the dependence on solely instinct and intuition when making decisions. Furthermore, Berndtsson, et al. (2018) depict three features characterizing a data-driven mindset. Firtsly, the presence of a "test and learn" environment where decision-makers conduct experiments and accept their results even if they are against their beliefs. Secondly, the chase of a correctly generated insight regardless of the job position of the person who discovered it. Thirdly, in accordance with what McAfee and Brynjolfsson (2012) suggest, the absence of an "instinct-based veto" against insights from data.

Human skills

The last element necessary to become data-driven is the presence of human resources skilled in terms of big data and BDA. In fact, enterprises need people capable of collecting, reporting data and observing it from different perspectives to understand its meaning and how it can be used (Ottanio, 2014). Moreover, they should be able to communicate results to decision-makers (Anderson, 2015), thus there should be collaboration and communication within the organization. The job profiles apt for these activities are usually placed under the name "data scientist" (Ottanio, 2014). In 2014, the European Commission projected that by 2020 around 100.000 new data-related jobs would have been created (European Commission, 2014). For this reason, many companies in different sectors are hiring data scientists, alaysists and data engineers as well as establishing new management roles at the C-level such as Chief Data Officer, Chief Analyst Officer and Chief Digital Officer (ibid.).

In order to provide a comprehensive view on elements characterizing data-drivenness it seems relevant to present a similar framework to the one depicted above, but that focuses on the real time big data flows, called digital data streams. In fact, other authors present four elements that companies willing to derive value from them need to build big data capability (Pigni, et al., 2016). The *mindset* refers to the presence of an organizational culture and strategy toward data-driven initiatives. The *skillset* describes the ability of a company to manage those initiatives, by combining business and technological capabilities. Moreover, the skillset comprises the capability of recognizing which data are relevant for driving decisions. The third element is the *dataset* that is the ability of detect and gather those real time data recognized as useful. The last is called *toolset* and it describes the competence to utilize proper hardware and software technologies to handle digital data streams and extract value from them.

Figure 3: Data-drivenness elements



(source: own elaboration)

2.3.2 Opportunities and challenges of data-drivenness

As the researcher did with opportunities and challenges of big data and BDA, it is important to state that the many of the ones of data-drivenness are, as well, sector and company specific as they depend on the activity of enterprises. Hence, the author will present those opportunities and challenges that are considered general and applicable to various contexts.

2.3.2.1 Opportunities

Accenture Labs (2018) describes the transformation toward data-drivenness as the "new table-stake for enterprises". In fact, the decisions taken in the light of big data are smarter, better targeted and tested (McAfee & Brynjolfsson, 2012). Already in 2012, a study conducted on 179 big publicly-traded companies highlighted that these defining themselves as data-driven were 5% more productive and more profitable than their competitors (Brynjolfsson, 2012). Moreover, thanks to velocity dimension of big data, decision-makers are allowed to rely upon almost real-time data, hence being able to undertake almost immediate actions improving not only the long-term choices but also the intraday ones (Mikalef, et al., 2018). In this perspective, by combining insights from different data sources, decision-makers might be able to early glimpse signals in the market, such as competitors' actions and industry trends (Sokolowski, 2018).

All in all, one can say that data-driven decisions are better decisions but it is meaningful to consider which are the factors influencing the quality of choices taken on the evidence from big data. In more detail, as in general the quality of something depends on the quality of inputs and of the transforming process from inputs to outputs, both data quality and the activities for processing, might influence the value of resulting decisions (Janssen, et al., 2017).

2.3.2.2 Challenges

Notwithstanding the opportunities coming from being data-driven, a recent survey conducted over 64 c-level technology and business executives of US companies revealed that the majority of partipants report that they have not yet embraced a data culture and data-driven organization even if almost everyone admits the importance of big data and BDA for their organizations, also in terms of investments (Bean & Davenport, 2019). Thus, it seems necessary to present which might be the challenges that companies face with respect to becoming data-driven. Anderson (2015) suggests to divide them into two categories: data-related challenges and culture-related challenges.

Data-related challenges mostly refers to the lack of trust that decision-makers have toward data due to skepticism about its quality (Anderson, 2015). This is clearly related to the need of addressing the reliability of data before making use of it, explained in relation to big data and BDA challenges (2.2.5.2). In this regard, an interesting study conducted by Deloitte, highlights that data quality management is a serious issue that poses the necissity of establish control data capabilities in organizations (Deloitte, 2018). In addition, the enormous volume of data as wells as the pace at which it generates, threats enterprises that requires ability to devise subsets of relevant data as well as improve processing power (Anderson, 2015). Again, Deloitte (2018) underlines that data management is a considerable challenge for studied companies.

Culture-related challenges refers to those that companies face in the changing mindset. According to a research conducted last year by NewVantage Partners (2018) about the use that companies make of big data, the main issues that prevents companies from its successful adoption are the cultural resistance to change and the difficulty related to adaptability to change. More in detail, a key inhibitor of becoming data-driven can be viewed in the attitude of enterprises to value intuition (Anderson, 2015). In this context, it could be related to the circumstance where companies often rely on HiPPO, the Highest-paid person's opinion by letting decision-makers take decision regardless of what data says (McAfee & Bryinjoilfsson, 2012). This is also in line with another culture-related challenge presented by Anderson (2015): the lack of accountability. It refers to the fact that sometimes it seems that decision-makers are not held accountable for their decisions. Thus, it does not matter who takes decisions and how, incurring in the risk of problems approached and solved in a subjective manner. Lastly, the lack of data literacy has been considered challenging since often decision-makers do not have enough knowledge to understand how data has been collected and analysed before arriving in their hands. This poses the risk of not being able to interpret data correctly and use them to guide their decisions (The Economist, 2018).

2.4 Organizational change

2.4.1 Defining organizational change

In the previous sections of this study, three main phenomena have been analyzed: digitalization, big data & BDA and data-drivenness. Each of these is likely to entail changes in organizations dealing with them. In particular, digitalization has been considered as the surrounding in which enterprises are operating and it involves fundamental changes for them, due to the application of new digital technologies in day-to-day activities (Parviainen, et al., 2017; Andersson & Rosenqvist, 2018). In that context, big data and BDA, considered as new technologies, could require need to change for organizations willing to adopt them because their introduction necessitates new skillsets, adapted culture as well as top management support (Halaweh & Massry, 2015). Finally, data-drivenness presumably requires several organizational changes for its realization. As a matter of fact, although potential benefits of data-drivenness are known, many companies find it difficult to become data-driven due to resistance to change and difficulties in adaptability (NewVantage Partners, 2018).

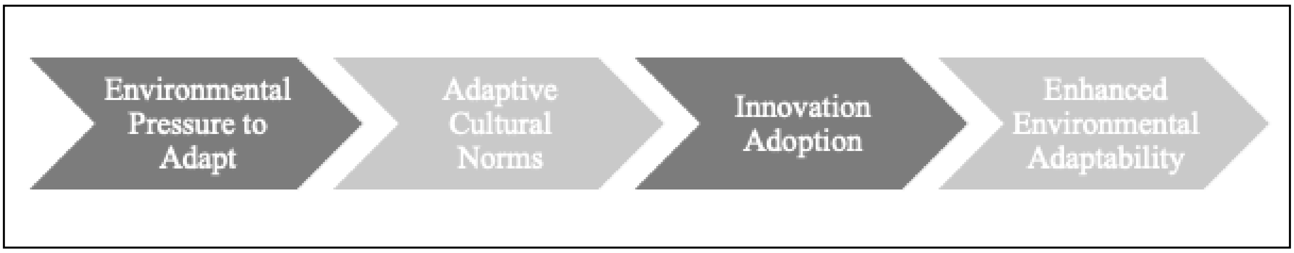
In this light, in order to answer the question subordinating the main one, it seems relevant to present a background on organizational change. Before starting, it is necessary to point out that the theory that will be presented below is non-exhaustive given the wideness of this topic that applies to many social science disciplines. Thus, the author will present some aspects of organizational change theories deemed to be relevant in the context of this study.

In a theoretical view, organizational change is defined as the process by which organizations shift from their current state to some desired state with the aim to increase effectiveness (Jones, 2013b). similarly, it is described as the transformation of an organization between two different moments in time (Barnett & Carroll, 1995).

In a more practical view, in order to remain competitive in the business environment companies need to constantly adapt to changes (Boss, 2016) as the core of management is dealing with modifications in the external environment (Chakravarthy, 1982). In fact, organizations have always been surrounded by new regulations, intensified competition and technological advancements (Kotter & Schlesinger, 1979). In particular, taking into consideration the external environment of organizations, many different forces provoke the necessity of change (Jones, 2013b) and technology is a major one. In fact, to maintain its efficiency an organization should adopt the latest technology, and this commonly determines changes to task relationships due to new skillsets (ibid.). In the context of this study, change could be caused by technological developments arising from digitalization and the creation of increasingly larger amounts of data to collect, analyze and exploit.

The process by which companies regularly adapt to changes has been defined using the term "strategic management", as reported by Chakravarthy (1982). In other words, "change management" is the process of constantly renovating an organization's strategy, structure and capabilities to deal with evolving environment (Moran & Brightman, 2000). These concepts are reported by Hannan and Freeman as "adaptation theory" which states that modifications in organizations happen in response to environmental changes, opportunities and threats. Moreover, they point out that an enterprise will be able to survive only if the speed of response is in line with the timing of changes of external factors (Hannah & Freeman, 1984). In this regard, Kitchell (1995) suggests a model of adaptation where corporate culture plays a fundamental role in enhancing environmental adaptation and the consequent innovation adoption. In detail, in the light of an environmental pressure to adapt, company develops the so called "adaptive cultural norms" that facilitate its capability of surviving by embracing new technologies as well as its enhanced environmental adaptability (Kitchell, 1995).

Figure 4: Linkages between Environmental Adaptation, Corporate Culture, and Innovation Adoption



(Source: Kitchell (1995, p.197))

According to the researcher, Kitchell's model seems to be suitable to explain the situation presented by this study. In fact, it is possible to believe that digitalization and in particular big data and BDA might exert environmental pressure to adapt. Thus, organizations probably need to adjust their culture in order to exploit their full potential by embracing data-drivenness, such as by developing a mindset where intuition is not everything and where there is collaboration across company to share insights.

In an akin line as the one proposed by Kitchell (1995), Mirvis, et al. (1991), suggest that there are two main factors to consider when introducing a new technology: user attitude and experience and organizational culture (Mirvis, et al., 1991). The first refers to the importance of being ready to use it by updating skills and way of working. The second refers to the impact of employees' experiences on the way they perceive the change provoked by its introduction.

2.4.2 Resistance to change

Notwithstanding the importance of change for organizations willing to remain competitive in the evolving business environment, many companies fail in this attempt or, at least, find it difficult. An example has been provided when explaining data-drivenness challenges (section 2.3.2.1).
According to many authors, one of the main reasons for complications encountered during the changing process is resistance to change or inertia (Jones, 2013b). As reported by Pardo del Val and Fuentes (2003) in their literature review on this topic, Ansoff (1990) defines resistance as a circumstance that impacts on the change process, “delaying or slowing down its beginning, obstructing or hindering its implementation, and increasing its costs” (Pardo del Val & Martinez Fuentes, 2003, p.148).

Kotter and Schlesinger (1979), highlight several factors that might cause resistance to change within organizations. Among these, the willingness not to lose something valuable and the low level of tolerance. In fact, on one hand people might fear they can lose something that they really care about as a consequence of change. On the other hand, low patient might derive from the anxiety toward the necessity of developing new skills and adjusted behaviours after the adaptation. In the context of data-drivenness, indeed, individuals could worry of losing the possibility of use solely intuition and, particularly, high-level managers might fear the loss of strong decision-making power. Moreover, both the new skillsets and the mindsets required, probably lead to low tolerance. As a matter of fact, Lawrence (1969) distinguishes two aspects of change creating resistance and that seems to be applicable to this context. The first is what he defines as technical aspect which refers to modifications in the way of working due to the adoption of new technologies (Laurence, 1969). The second is called social aspect and it concerns changes in relationships across people in the organization (ibid.).
To conclude, it is important to clarify that stating that organizations are characterized by resistance to change and inertia, does not mean that they never change. It means that often they respond slowly to external forces (Hannah & Freeman, 1984).

2.5 Summary of literature review

In order to facilitate the reading process of the following chapters, the author decided to include a brief summary of the literature review. The aim is to highlight the main theoretical aspects that the author referred to when conducting the data collection, analysis and to reach final conclusions. The literature review covers theory about digitalization, big data and big data analytics, data-drivenness and organizational change.

In section 2.1 definitions and interpretations of digitalization are presented since, in this study, it has been considered as the sorrouding in which companies are currently operating. Moreover, the principal benefits and challenges are explained. Finally, the relation between digitalization and big data & BDA is highlighted.

In paragraph 2.2 the author reports theory about big data and big data analytics. In detail, big data meanings are reviewed given the lack of a unique definition. Moreover, since the author noticed that the dimensional aspect of big data and the technical aspect of BDA are common factors in definitions, these are deeply addressed. In addition, in order to give the reader an understanding on how companies work with data to create value, the big data value chain is explained. Lastly, the main opportunities and challenges are addressed.

In section 2.3 data-drivenness is introduced by reporting various definitions given that a unique academic framework apt to explain data-drivenness seems not to have been developed, yet. Furthermore, the author covers the main elements characterizing a data-driven company. Finally, opportunities and challenges are outlined.

In paragraph 2.4, the researcher displays some theories about organizational change deemed pertinent to the studied context. In particular, adaptation and resistance to change theory and models are presented.

Table 2: Summary of literature review

2.1 Digitalization: definitions and interpretations; main benefits and challenges; relation with big data and BDA
2.2 Big Data and Big Data Analytics: big data definitions review; dimensions; big data analytics; big data value chain; opportunities and challenges
2.3 Data-drivenness: definitions; main elements; opportunities and challenges
2.4 Organizational change: relevant aspects and definitions; adaptation theory and models; resistance to change

3. Methodology

This chapter presents the methodology used to conduct this research. In particular, decisions in relation to research strategy and research design are motivated. Moreover, the data collection and data analysis processes are explained. Finally, the chapter entails a discussion about the quality of the research.

3.1 Research strategy

3.1.1 Qualitative Research Strategy

The research strategy can be quantitative or qualitative and the decision on which one to follow is based on the nature of research problem and the purpose of the analysis (Creswell, 2014). Given the fact that the aim of the research is to explore *how* B2B companies in the telecommunication sector operating in the digitalization era are dealing with data-drivenness, qualitative research strategy seems to be more appropriate. Moreover, the choice of such research strategy is in line with the author's purpose of qualitatively contributing to existing studies on this topic as explained in the introduction section (paragraphs 1.2 and 1.3)

In fact, qualitative research strategy enables the researcher to gather opinions, insights and point of views of respondents around the analyzed topic (Bryman & Bell, 2011) and it is what the researcher is searching for in this thesis. In particular, it allows to take into consideration the specific context of respondents enabling them to represent their meanings about specific situations rather than values and perceptions of the researcher (Yin, 2011). In the context of this research, the author aims also at finding benefits, challenges and future expectations about big data, big data analytics and data-drivenness from companies' point of view, empowering them to express their considerations. Thus, the purpose is to find results expressed in words rather than in numbers, avoiding quantification and allowing the emergence of unforeseen information during the research process.

Finally, qualitative strategy is chosen since it offers more flexibility of the research thanks to the possibility of making adjustments and corrections when needed.

However, it is important to take into account the critiques related to qualitative research strategy. In particular, the cons are mainly four (Bryman & Bell, 2011) . Firstly, it is considered too subjective since it relies on personal decisions of the researcher. In this thesis the author is aware of the personal bias that might be a source of issues in qualitative studies. Hence, this factor will be taken into account all through the study to attenuate the potential negative effect.

Secondly, it is difficult to replicate a qualitative study given the lack of standard procedures to follow and given the fact that it is hard to replicate interviews. However, this does not affect the outcome of this research since replication is not the main purpose of this study.

Thirdly, problems of generalization have been recognized since qualitative research usually focuses on small samples. Notwithstanding, given the nature of the chosen research design being multiple case study, the objective is not to create a general theory applicable to different contexts but rather to focus on cases, gathering in-depth information. Thus, this critique seems not to be pertinent to this study.

Ultimately, the last argument is that there could be a lack of transparency of data collection and analysis. However, the researcher aims at minimizing the deficiency of clearness by keeping track of the entire research process and by giving clarifications on the actions and decisions taken on each stage until conclusions are reached.

Lastly, qualitative research strategy is usually associated with inductive approach as opposite to deductive approach. However, according to Bryman and Bell (2011) this distinction is not clear-cut. In fact, often qualitative research does not create theory and it uses theory as background (Bryman & Bell, 2011).

In general, inductive approach conceives the fact that data guide the emergence of concepts (Yin, 2011) while deductive approach is used to test hypothesis with empirical scrutiny (Bryman & Bell, 2011). As the aim of this research is not to test hypothesis or theories but rather to explore the topic through the collection of opinions to generate concepts, the inductive approach seems to be more feasible.

3.2 Research design

3.2.1 Multiple case study design

In order to answer the research questions of this study a multiple case study design appears to be appropriate. Bryman and Bell (2011) define it as a typology of comparative design used when the research strategy is qualitative and when more than one case is analyzed. Such design is widely used in business research and it usually takes two or more organizations as cases for the comparison (Bryman & Bell, 2011). Moreover, in the context of this study, this typology of research design is deemed more appropriate than a cross-sectional design since the purpose is to deeply focus on specific cases rather than on their general surrounding to obtain a generalizable result.

Moreover, comparison between different companies might be useful to gather several perspectives around the topic. In particular, a more comprehensive view could be obtained by analyzing four cases and by comparing them. In fact, multiple case study design enables a wider analysis to answer the research question (Gustafsson, 2017) and it allows the researcher to firstly focus on specific context of each case and then to compare them.

Finally, the chosen design is capable of providing strong and reliable evidence (Baxter & Jack, 2008), important elements as far as the quality of research is concerned.

Nevertheless, as for the selection of the research strategy, it is necessary to consider the critiques to multiple case study design. Baxter and Jack (2008) believe it is too time consuming to implement, indeed the limited time span is a limitation of this research. Moreover, Bryman and Bell (2011) argue that the researcher might focus more on gathering differences among cases rather than on specific contexts along with the fact that there might be the need of taking a specific point of view from the beginning. However, in this thesis through the use of semi-structured interviews (section 3.3.2.2) the researcher focuses on specific contexts while enabling terms of comparison as well as the possibility of answering in an open manner regardless the initial point of view taken.

3.2.2 Selection of case companies

In collaboration with FTK the researcher selected Swedish-based B2B companies in the telecommunication sector: TalkPool AB, Ericsson, GothNet and Telia Carrier. To be precise, the focus on Sweden constitutes a geographical limitation as reported in paragraph 1.6. Moreover, as explained in the presentation of case companies (paragraph 1.5), these pertain to the same sector, but they perform different activities, have different sizes and are present in Sweden since different moments in time. For the sake of clarity, the size is evaluated based on the number of employees since this is the most common criteria used for this purpose (OECD, 2019).

3.3 Research method and data collection

Data necessary to address the research questions of this study have been gathered from both primary and secondary sources. Primary sources are defined as information related to the specific research problem, disclosed by the researcher him/herself for the first time (Rabianski, 2003; Hox & Boeije, 2005). On the other hand, secondary sources are not directly collected by the researcher and are available from other studies (Rabianski, 2003).

3.3.1 Secondary data

To provide a theoretical background to this master thesis, the collection of secondary data is performed as part of the literature review. Bryman and Bell (2011) explain the literature review as being useful to build the foundation on which the researcher justifies the research question and selects the research design. Moreover, it enables the author to select the right data collection and analysis methods (Bryman & Bell, 2011). Therefore, the collection of secondary data has been conducted at the beginning of the research process.

In order to search for existing literature on the above-mentioned topics, the following keywords have been utilized: "digitalization", "digital transformation", "effect of digitalization", "drivers of digitalization", "big data", "benefits big data", "opportunities of big data", "challenges big data", "big data analytics", "business analytics", "data-driven culture", "data-driven organization", "data-drivenness", "data-driven decision making", "decision making with big data", "organizational change", "organizational adaptation", "resistance to change".

Moreover, journal articles, reports, magazine articles and books have been collected through Google Scholar, University of Gothenburg Library and LUISS Library. To be precise, the author used reports from consultancy firms for topics where a lack of academic and scientific literature was observed. The secondary sources are either in English or in Italian and the majority have been extracted from digital sources.

Ultimately, a clarification on how the literature review has been conducted needs to be given since Bryman and Bell (2011) distinguish two methods: systematic review and narrative review. Systematic review is defined as a detailed process aimed at minimizing biases by conducting an exhaustive review of scientific articles (ibid.). Indeed, when conducting systematic review researchers set out specific inclusion and exclusion criteria. Differently, narrative review entails a broader scope and less specific criteria and it is usually used to acquire initial knowledge related to the topic addressed through the research (ibid.).

In the context of this master thesis, narrative review was regarded more applicable given the limitations of the systematic review presented by Bryman and Bell (2011). Firstly, the systematic review is less suitable for qualitative researches that requires greater flexibility to modify bounds of the study compared to quantitative researches. Secondly, it is argued that systematic review is time and resource consuming, thus less feasible for a student research project.

3.3.2 Primary data

In order to answer the research and sub-research questions primary information has been collected both from experts and from case companies.

3.3.2.1 Sampling and selection of respondents

The sample of a research is defined as the part of the population that is chosen for analysis and it can be selected by using a probability or a non-probability approach (Bryman & Bell, 2011). Usually, qualitative research strategy entails non-probability sample, where the respondents are selected without a random selection and based on the researcher's judgment (Saumure & Given, 2012). Saumure and Given (2012) present three common non-probability sampling methods which are convenience sampling, snowball sampling and purposive sampling.

For the aim of this research, a purposive sampling is chosen. It involves the selection of respondents that are competent and knowledgeable in this study field, able to provide relevant information to answer the research question (Etikan, et al., 2016). In the context of this thesis, a purposive sample is used both for the selection of experts and for case companies' representatives. For the sake of clarity, the sample has mostly been chosen with the collaboration of FTK. Furthermore, respondents have been contacted via email when FTK acted as intermediary or via LinkedIn otherwise (see in appendix the message used to contact them, respectively appendix 1a and appendix 1b).

As far as the experts, the author selected people whose position in their companies was considered to be in line with the aim of the research. To be clear, an expert is defined as "a person with a high level of knowledge or skill relating to a particular subject or activity" (Cambridge Academic Content Dictionary, 2019 a)). More in detail, respondents from the big Swedish corporation (anonymous) and IBM were chosen given both their positions and backgrounds concerning IT but in two different typologies of companies, in order to acquire diverse perspectives. Furthermore, the focus group with two respondents from Meltwater was done in the light of the activity performed by this IT company that develops solutions in order to help enterprises in analyzing external unstructured sources of data and use them to inform their decisions.

The detailed list of expert respondents is provided below.

Table 3: List of expert respondents

Respondent	Title	Company	Date	Method	Length
Anonymous[2] Expert (respondent A)	Senior manager innovation & digital services	Big Swedish corporation	2/04/2019	Face to Face interview	50 min
Peter Heurling (respondent B) **Nicolas Westdahl (respondent C)**	Enterprise Solutions Director, EMEA Head of Services and Support, Enterprise EMEA	Meltwater	8/04/2019	Face to face interview (focus group)	1h and 10 min
Frode Langmoen (respondent D)	Technology executive	IBM	12/04/2019	Face to face interview	1 h

As far as case companies, the researcher interviewed their representatives as well as decision-makers with the aim of obtaining deep understanding, insights, opinions and perspectives about the topic within each enterprise. For the sake of precision, a decision-makers is qualified as “a person who decides things, especially at high level in an organization” (Cambridge Business English Dictionary, 2019 b) while a person is a representative when he/she represents another people or group (Cambridge Academic Content Dictionary, 2019 b). As a matter of fact, selected respondents were deemed to be able to contribute to the study helping the author to answer the research questions.

The detailed of case companies’ respondents is provided below.

[2] The respondent asked to be anonymous, so the name and the company are not disclosed.

Table 4: List of case companies' respondents

Respondent	Title	Company	Date	Method	Length
Boris de Bruin (respondent E)	Responsible marketing and sales	TalkPool AB	13/03/2019	Face to Face interview	45 min
Stefan Lindgren (respondent F)	CEO CTO	TalkPool AB TalkPool Group	13/03/2019	Face to Face interview	55 min
Jonas Wilhelmsson (respondent G)	Head of Ericsson Garage	Ericsson	1/04/2019	Face to Face interview	1hour and 10 min
Lars-Erik Lindberg (respondent H)	Innovation leader Ericsson Garage and change leader in R&D department	Ericsson	4/04/2019	Face to Face interview	50 min
Magnus Hartmann (respondent I)	Business developer in sales and marketing department	GothNet	1/04/2019	Face to Face interview	1 hour and 15 min
Per-Olof Odgren Lundh (respondent L)	IT Network specialist and system engineer	GothNet	11/04/2019	Face to Face interview	50 min
Per Brännström (respondent M)	Director of business analysis in voice trading area	Telia Carrier	5/04/2019	Phone	55 min

On the whole, the selected respondents are perceived to be reliable either because some have been contacted through the mediation of a trustworthy firm such as FTK or given their position in the company.

3.3.2.2 Interview methods

The interview method chosen to conduct this research is semi-structured interviews. Before opting for it, the researcher faced the need of choosing among different methods of data collection. Bryman and Bell (2011) identifies mainly three methods for collecting data in qualitative research: focus group, ethnography and participant observation and interviews. The first method concerns a group interview with several participants on a specific topic. The second entails the protracted involvement of the researcher in the context of his or her studies, in order to conduct a deep studying observing behaviors. The last method refers to the interviewing process that the researcher implements. More in detail, interviews can be unstructured or semi-structured and it will better be analyzed later on in this paragraph.

Having considered the characteristics of the three methods proposed by Bryman and Bell (2011), the researcher decided to use the interview. In fact, on one hand, the ethnography and participant observation seemed not to be applicable given the limited time span of this research. On the other

hand, the focus group was considered not feasible given the research design being a multiple case study, entailing that respondents are from different companies.
Notwithstanding this, the author conducted a small focus group with two respondents from Meltwater, as part of the collection of empirical findings from experts. This choice enabled the author to acquire opinions of two experts at the same time, favoring their direct confrontation thus obtaining even deeper insights with respect to single interview. In fact, the main advantage of focus groups discussed by Bryman and Bell (2011) is that it allows respondents to expose their perspectives in a different manner with respect to individual interviews since participants interact with one another. However, this method is characterized by some limitations. In particular, the interviewer could have lower control of the group interview than in the individual and data might be difficult to collect (Bryman & Bell, 2011). In order to overcome these issues and as it is explained later on in this paragraph, the researcher has used semi-structured interview in order to be able to guide and moderate the focus group. In turn, this facilitates the organization of data collected as the researcher had some already prepared categories. Moreover, since the focus group included a small number of respondents, the interviewer was able to ask almost the same questions to both of them.

As anticipated above, as far as interview method is concerned, the one used is semi-structured interviewing. Semi-structured interviews find ground on a set of prepared and open questions that guide both the interviewer and the respondent (Flick, 2018). In the context of this research, semi-structured interviewing seemed more appropriate than unstructured interviews given that the research has a relatively clear focus and that the need of comparability among interviews seems necessary for the analysis. In fact, Bryman and Bell (2011) explains that in case of multiple case study design, researchers usually select semi-structured interview method in order to ensure "cross-case comparability". Also, this research method enables the right trade-off between focus and flexibility, given by the fact that the interviewer can adjust the interview as it goes on, based on the interview guide (Bryman & Bell, 2011).

3.3.2.2.1 Interview guide

Given the fact that the data collection method chosen was semi-structured interviewing, the researcher has prepared an interview guide, one for experts and one for companies' respondents (appendix 2a and appendix 2b). Each interview guide has been prepared in accordance to the rules suggested by Bryman and Bell (2011). It covers the main points that were to be explored during the interviews in order to answer the research questions. Hence, the interview guide is built in such a way that more general questions are asked at the beginning, to then moving toward more in-depth questions related to the subject of the study. Indeed, the first questions are aimed at investigating how respondents define big data and big data analytics and data-drivenness in their organization. It then continues by examining how respondents' companies have been affected by the big data, big data analytics and the related adaptation process. It progresses to find out the benefits and challenges related to data-drivenness faced by companies. Finally, it concludes with questions about future expectations about the studied area.

3.3.2.2.2 Conducting interviews

As mentioned above (section 3.3.2.2), the researcher decided to conduct semi-structured interviews (see above the list of respondents Table 3 and Table 4). Before performing the interviews, respondents received a short synopsis of the thesis in order to have an overview and they were given the possibility of receiving the interview guide in advance.

Out of the eleven interviews, ten were conducted face-to-face at companies' respondents' offices while one was conducted by phone. All the interviewees were given the faculty of deciding the specific place for the interview. Spaces and rooms selected by respondents were quiet and booked for the purpose of the interviews and this is something extremely important according to Bryman and Bell (2011), since the respondent has the possibility to better express is thoughts and opinions. In the only case of phone interview, both the interviewer and the interviewee were in silent and private places so that there were no distractions and noise.

All interviews were recorded with the consensus of the respondents, who also could decide whether to be anonymous or not, and in the majority of cases the researcher was accompanied by a colleague who was entitled to take notes during the interview. This enabled to speed up the process of reporting the empirical findings as well as increased the level of reliability. In fact, given the transcription being very time-consuming (Bryman & Bell, 2011), the researcher decided to send back to respondents a summary of the interview already arranged in the categories of the empirical findings so that they had the possibility to validate it. Moreover, the summary already contained quotes from the interview, that the author was able to get thanks to both the record and the assistance of notes taken by the colleague.

3.3.3 Presentation of data collection

Given the multiple case study design with the addition of findings from experts, empirical findings from semi-structured interviews are presented by expert and by company in order to provide the reader with a deep understanding of each context.

Data collection is articulated in three main categories that the author generates based upon the literature review and the interview guide: (1) big data and big data analytics; (2) data-drivenness and

(3) organizational change; with some subcategories. The utilization of such categories facilitates both the presentation of data collected and data analysis, since they enable comparability. Finally, a table summarizing empirical findings is provided where the reader can find the main points addressed by the interviewees.

3.4 Data analysis

Data analysis entails the comparison between empirical findings, obtained during the data collection both from experts and case companies' representatives and theoretical findings covered in the literature review. The objective is to figure out to what extent theory and reality are in accordance with each other. Moreover, since the research design at stake is a multiple case study, data analysis is also aimed at comparing and contrasting the empirical results across cases, to gather similarities and differences on how selected companies are dealing with data-drivenness and how they are changing in this light.

Data analysis is structured in the same categories and sub-categories of empirical findings in order to guarantee a level of comparability. Patterns of analysis are defined based upon the main points expressed by the interviewees.

Altogether, during the analysis the author executes critical thinking in order to reason around some relevant aspects. This enables the researcher to answer the research and sub-research questions in a satisfactory manner, reaching the final conclusions of the study.

3.5 Research quality

As far as quality of qualitative research is concerned, some suggest using the same quality criteria of quantitative research namely reliability and validity by adjusting them (Bryman & Bell, 2011). However, according to others in order to evaluate the quality of qualitative research other two criteria should be considered: trustworthiness and authenticity (Bryman & Bell, 2011). This thesis takes into account the latter view.

3.5.1 Trustworthiness

Trustworthiness concerns the level of confidence in data, analysis and procedures used to guarantee quality of research (Connelly, 2016). Bryman and Bell (2011) present the four sub criteria identified by Lincoln and Guba to determine trustworthiness of research: credibility, dependability, confirmability and transferability.

Credibility, equivalent to internal validity in quantitative research, is the confidence in the veracity of the study and its outcomes (Connelly, 2016). In order to ensure credibility Bryman and Bell (2011) suggest following rules of good practice and using the respondent validation and triangulation techniques. In conducting this study, the researcher used the respondent validation by sending to each interviewee a summary of the findings in order to allow them to control. What is to be noticed is that the summary of interviews has been created based upon the audio recording straight after each interview so that the researcher still had everything in mind. Moreover, if during the interviews something was not clear, the author asked for explanations and clarifications. Finally, the author studied literature about the topic in a scrupulous manner in order to be able to ask proper questions during the interviews, enhancing credibility.

Dependability, corresponding to reliability in quantitative research, entails the stability of data “over time and over the conditions of the study” (Connelly, 2016). In the context of this research, dependability can be achieved by what Bryman and Bell (2011) define as “auditing approach”. It refers to the author’s activity of keeping track of all the phases of the research process from the beginning to the end so that it is possible to evaluate to what extent proper procedures have been adopted. Hence, the author adopted a systematic approach for data collection and analysis with the aim of enhancing dependability of the research.

Confirmability, similar to the objectivity of quantitative research, refers to the neutrality of findings as well as their degree of repetition and consistency (Connelly, 2016). Completely avoiding subjectivity in business research is almost impossible but the author tried to conduct the study by preventing the influence of personal beliefs over the research and its outcomes.

Transferability, associated with generalization in quantitative research, is the ability of transferring the findings in other circumstances and, since qualitative research usually deeply studies a small sample, it is limited (Bryman & Bell, 2011). This research entails a comparative study among Swedish companies operating in the same sector but performing different activities, with diverse size and a different newness to the Swedish market. Thus, findings might not be completely generalizable, but they could work as guidelines for data-drivenness for organizations in similar conditions.

3.5.2 Authenticity

Authenticity is described according to five different criteria namely fairness, ontological authenticity, educative authenticity, catalytic authenticity and tactical authenticity (Bryman & Bell, 2011).

Fairness relates to the fairly representation of different viewpoints and since this study aims at interviewing decision-makers in the selected organizations, fairness might be present.

Ontological authenticity refers to the ability of the study of providing a better understanding of the social context and this research aims at being ontologically authentic by contributing in the understanding of the social context regarding data-drivenness in organizations.

Educative authenticity relates to research' ability of helping members of the social context to understand other members' opinions. This criterium seems to be satisfied given the study being a multiple case study with several interviews and that the report will be shared with selected companies.

Catalytic authenticity concerns the capability of the research of pushing members to take actions to change their circumstances and since the study is not aimed at generating a framework, it might be low.

Tactical authenticity refers to the ability of the study of guiding the members toward the first steps of action. Since the primary aim of this research does not lie in suggestions of actions, tactical authenticity appears not to be relevant.

4. Data collection

In this chapter the data collection from primary sources is presented. The findings from semi-structured interviews are displayed per expert and per case company in order to provide a comprehensive view of each. Moreover, at the beginning of data collected from experts their brief presentation is provided while enterprises have been already introduced presentation of case companies (paragraph 1.5) Findings are divided into three main categories namely (1) Big Data and Big Data Analytics; (2) Data-drivenness and (3) Organizational change and some sub-categories. These are derived from literature review and interview guide. Lastly, in order to streamline the understanding of empirical findings, the author includes a summary table at the end of the chapter showing the main points expressed by respondents.

Data collected from experts

4.1 Senior manager innovation and digital services at Big Swedish corporation

The interviewee is working at her company since 2005 and now she is a senior manager innovation and digital services and she is mainly focusing on developing innovative ideas enabled by Information Technology (Anonymous expert, personal communication, 2019). She has a master's degree in informatics and a Master of Science at the IT university of Gothenburg in the same field (Anonymous expert, personal communication, 2019).

4.1.1 Big Data and Big Data Analytics

4.1.1.1 Defining Big Data and Big Data Analytics

Respondent A defines big data as a way of finding patterns and utilize them in order to discover new things and create new types of services. Moreover, putting in relation digitalization and big data, interviewee A perceives that in a more digitalized world where devices are more connected, an increasing amount of various type of data is generated. In this context, the analysis of data creates many possibilities

According to respondent A, drawing the line between data and big data is very difficult because some dimensions changed compared to the past.

4.1.2 Data-drivenness

4.1.2.1 Defining data-drivenness

Respondent A defines a data-driven company as one that *"utilizes data as an asset by gaining value from it in some way"*. According to the respondent, *"you must have data-driven decisions within different parts of the company"*. Moreover, when it comes to strategic decisions, companies couple insights used from external data from competition and trend analysis with some internal data.

Interviewee A perceives that everyone across departments should have access to data. However, she presents a backside of this by explaining that data can be manipulated, and it can be very dangerous. In particular, she adds that especially in big companies with many systems having control over all data sources, thus sharing them, might be hard.

As far as the mindset of a company, respondent A believes that considering data valuable as other company assets is crucial. In this sense, she perceives that within the company data should be understood as having high potential in supporting the company to build new strategic decisions and survive.

4.1.2.2 Opportunities of data-drivenness

According to the respondent, the main opportunity of data-drivenness relates to take better and more accurate decisions. Moreover, other opportunities refer to the benefits arising from big data usage, such as the possibility of find new innovation avenues and the capability of understanding customers' behavior, thus targeting their needs. Furthermore, when asked about B2B companies, respondent A states that this type of enterprises can collect and use a lot of data, thus is not a prerogative of B2C ones. She provided the example of increasing automation within the construction industry thanks to data from different sources.

4.1.2.3 Challenges of data-drivenness

Challenges are perceived by interviewee A to be related to the use of big data. Indeed, she believes that some of them pertains to the privacy legislation and she mentions the GDPR[3]. Moreover, she believes that handling and mastering big data could be difficult. With this regard, respondent A states that there is the need of having capabilities to understand data in order to avoid wrong data-driven decisions. She also points out that in big companies the risk of conflict of interests as well as misunderstanding across departments and functions increases if employees are not capable of correctly interpret data.

Moreover, respondent A says that it could also be a cost- related issue because extracting data requires investments that a company undertakes only if it glimpses tangible opportunities.

Finally, she thinks that reliability of data is a challenge, meaning that data can be manipulated. Thus, she highlights the need of *"data securitization"*. In fact, she explains that if a decision-makers bases his/ her decisions on manipulated data, that might result in wrong decisions.

[3] General Data Protection Regulation: data protection rules for all companies operating in EU. It gives to people control over their personal data and to businesses the possibility to benefit from a level playing field (European Commission, 2018)

4.1.2.4 Future expectations on data-drivenness

Interviewee A believes that companies that will not be able to become data-driven, will probably not survive because the entire society will become increasingly affected by the creation of more data. Moreover, during the discussion about HiPPO concept, she points out that this concept is likely to change since decision-makers at different positions can take decisions based on evidence from data.

4.1.3 Organizational change

4.1.3.1 Defining organizational change

According to respondent A, embracing digital tools entails an adaptation process that companies undertake by gradually adopting more digital technologies across various activities. In this perspective, she believes that adapting to digitalization is the result of an external pressure that companies face in order to remain competitive in the market and strengthen the brand positioning. In fact, respondent A suggests that digital tools might help in changing and renovate the current business model.

Another element pointed out during the interview is the organizational change resulting from the adoption of new technologies such as BDA. In particular, she thinks that new roles such as analytics and data scientists are created within companies because new skills are required with respect to the past. Moreover, she adds that some enterprises are creating *"more heavy roles"* in this fields, such as chief digital officer. Thus, according to respondent A, companies will phase changes in order to become data-driven and the constant change should be supported by organizational culture that enables the adaptation process. In this sense, she explains that culture *"is reflected on how people behave"* and take decisions for instance whether there is a centralized or decentralized decision-making process. Also, she thinks that changing the culture requires leadership because the top-management should guide the change.

With respect to the role of top management support in data-drivenness, interviewee A perceives that the process of becoming more data-driven is often a bottom-up process where the value of data is perceived more at lower levels of enterprises than at the top.

4.1.3.2 Resistance to change

When addressing resistance to change, respondent A points out that it is part of change in many enterprises because people might be afraid of changing in their roles within the organization as well as of new rules and processes that are likely to be created within it. In this perspective, she provides the example of companies that before had project leaders whose role has changed nowadays and has been reduced.

4.2 Focus group with Meltwater representatives

Founded in 2001, Meltwater is an IT company operating in more than 50 countries worldwide, among which Sweden (Meltwater, 2019). Actually, they are developing solutions in order to help companies in analyzing external unstructured sources of data and use them to inform their decisions (ibid.).

4.2.1 Big Data and Big Data Analytics

4.2.1.1 Defining Big Data and Big Data Analytics

Respondent C defines big data as made of two components: internal and external data. The former refers to data that a company collects from its internal activities such as the purchase behavior of customers. Respondent B describes it as the one *"in the four walls of firms".* The latter refers to data produced in the internet that is available to the public such as social media or editorial content and to data stored in databases such as patents. In considering the amount data, they discuss the comparison between big and small companies by stating that it is relative to the size of the company. Indeed, according to them, the amount is huger when it comes to external data of larger corporations with strong brands.

According to interviewee C, BDA involves the analysis of data using a vast array of technologies, from the simplest ones using search query[4] (such as Boolean search) to more advanced and efficient ones like machine learning and AI. Moreover, he points out that depending on *"what you are looking for"*, you can use different types of technologies. For instance, respondents provide the example of analysis of editorial contents in order to find metadata[5].

4.2.2 Data-drivenness

4.2.2.1 Defining data-drivenness

Respondents B and C agree on defining a data-driven company as one that takes decisions based on data and real-time information. In that sense, interviewee B clarifies that collecting data is not enough, because the main element is to combine different sources of data (external and internal) to support decisions and that is valid both for small and large companies, as well as for B2C and B2B. For instance, interviewee B clarifies that smaller companies in telecommunication sector might be interested in external sources such as locations while some of their big B2B clients use insights from external data from social media and editorials. In particular, Meltwater helps them in analyzing how many times people on social platforms speak about them or how many times the company name

[4] "Words that are typed into a search engine in order to get information from the internet" (Cambridge Business English Dictionary, 2019 a)

[5] "Metadata is data that describes other data. Metadata summarizes basic information about data, which can make finding and working with particular instances of data easier" (WhatIs.com, 2019).

appears in online news. In this perspective, respondent B points out that many B2B companies are focusing on aggregating both internal and external data in one platform.

Respondent B perceives that a vast portion of decision-makers is still taking decisions based on intuition but "*its role is decreasing over time*". In this sense, both believe that usually within a company there are departments and functions more data-driven than others. In particular, interviewee C believes in data-driven enterprises there is a *"collaboration"* between the analytical and the decision-making part.

4.2.2.2 Opportunities of data-drivenness

According to Respondent C, a great opportunity of data-drivenness relates to forecasts development. In fact, "*by combining historical internal data with real-time external information*" about competition and market trends, companies can develop more accurate forecasts. Moreover, respondent B illustrates an example of external sources of data about competition that might help companies in taking the right strategic decisions: job posting. Briefly, he states that if an enterprise observes that a competitor is hiring skilled engineers in a particular technology, it gets insights to decide whether to focus on that technology or to follow a different path.

In this logic, they believe that decisions informed by insights from data are better targeted. For instance, interviewee C explains that the business development function has the opportunity to develop a strategic plan based on insights from data while respondent B provides the example of enhanced new product development decisions.

All in all, they conclude that the main opportunity arises from the possibility of gaining competitive advantage.

4.2.2.3 Challenges of data-drivenness

Both agree that data privacy is the main challenge for data-driven enterprises. In this sense, respondent B perceives the likelihood of limitations in the amount of data that companies can exploit as a risk. Furthermore, for companies a challenge lies in the lack of trust on what data suggests.

4.2.2.4 Future expectations on data-drivenness

Interviewee B believes that the future will be characterized by the creation of new and more advanced technologies. He thinks that today companies can analyze what it has happened and what is going on, by seeing trends but the "*AI revolution"* will entail a support to help decision-makers in understanding for what they can use these insights. In this line, Respondent C states that at the moment *"AI is not enough smart"*. Moreover, interviewee B projects that probably in 15 years, 90% of decision-makers will use less intuition and more data insights. Similarly, Respondent C perceives that prescriptive analytics will enhance decision-making processes between two or more options. Finally, he believes that companies will increasingly rely on external data to inform their strategic decisions.

4.2.3 Organizational change

4.2.3.1 Defining organizational change

According to respondent B, companies need to adapt to digitalization, big data and BDA. In particular, he explains that information travels so fast that companies able to take strategic decisions in real-time, can have a competitive advantage. Moreover, he clarifies that taking decisions out of information is *"not something new, what is new is that there are many different and faster data points"*.

Respondent C perceives that some of their clients faced the need of change in order to intensify the use of big data, probably because there was an increase in awareness about its potential. In this regard, interviewee B mentions a difference between B2C and B2B companies. In fact, he believes that B2C have always used data from consumers in different activities while B2B traditionally used data only for marketing and communication strategies. Thus, the latter typology is now encountering more changes. Furthermore, both point out that traditional sectors like pharmaceutical face more difficulties in becoming data-driven with respect to other sectors such as telecommunication and finance, that have data included in their business.

Respondent C believes that becoming data-driven is a process where, step by step, all departments and functions will change to it, following a common vision. He thinks that in order to become more data-driven companies need to hire skilled employees such as analysts, invest in advanced technologies and ask for external support of companies like Meltwater.

Furthermore, in this process of change, in general top-management is perceived to be skeptical compared to lower level employees.

In analyzing the change according to company size, Respondent C perceives that for small and medium enterprises might be easier, *"they only need to buy a simple tool, they have proportionally less data and also less decision makers"*.

4.2.3.2 Resistance to change

According to both respondents, there could be some resistance to change for people working in a company since long time mainly due to inexperience, uncertainty and fear of doing things in different and new way.

4.3 Technology Executive at IBM

The respondent has a technical background in systems analysis and development. He spent around 22 years in IT industry, and he has been working at IBM for 25 years (Langmoen, F., personal communication, 2019). For the last 10 years he is working with startups, especially B2B.

4.3.1 Big Data and Big Data Analytics

4.3.1.1 Defining Big Data and Big Data Analytics

According to respondent D, big data is created by the combination of different types of structured and unstructured data. He clarifies that in the past companies mainly used structured data, easier to analyze. In particular, he explains that structured data is something that is contained in a database and that is easily searchable like sales while unstructured data refers to images, videos, text and data from social media, that are much more difficult to handle.

BDA is a *"way to see insights of all your data"*. He perceives that at the moment both B2B and B2C companies are starting to combine structured and unstructured data as well as internal and external data, where internal data refers to information collected from products and services of a company.

4.3.2 Data-drivenness

4.3.2.1 Defining data-drivenness

A data-driven company is one that can use data in order to "*get an advantage and to get more insights and better decisions"* both for automated operational and strategic decisions.

According to respondent D, there is a difference with respect to the past because before decisions were taken based on experiences and feelings of decision makers while now "*you have the facts and you can use models to use data in decisions"*. In this perspective, he states that data-drivenness involves a combination of data with knowledge and experience of decision-makers in almost every industry.

Interviewee D thinks that the main characteristic of data-driven companies is that they *"know that there is a value in data"*. Thus, they have skilled people *"to take care of that data and combine different types"*; infrastructure and architecture of data sources so they "*know where to get data and how to clean it to extract value"*. Furthermore, he suggests that such enterprises often have an *"open-mindset by being aware that the world changes over time, that they will be pressured from everywhere and that they need to appreciate and take care of that data"*.

According to respondent D, some departments are more data-driven than others and, depending on the data, they usually share data. In this perspective, a B2B company needs to make sure of data-securitization as it mostly uses data from its customers that are enterprises.

4.3.2.2 Opportunities of data-drivenness

According to interviewee D, data-drivenness in general enables to be more specific and precise in decisions such as in terms of targeting and business development.

4.3.2.3 Challenges of data-drivenness

The main challenge that interviewee D perceives is that if decision-makers are not able to understand data insights, they might take wrong choices. A related challenge is that *"data and models behind data could be manipulated*" both by internal and external hackers along the big data value chain. In this perspective, he explains that for companies combining different sources of data to inform their decisions, a challenge is that external and unstructured data might be not secure or trustworthy. In particular he points out that *"even if about 80% is internal data and 20% is external, this small proportion poses a lot of challenges".*

Moreover, a challenge outlined by respondent D involves international companies that must operate according to the laws of the countries where they are present and if these are different among each other, they face the challenge of operating in different ways based on it. This is a real issue especially in the context of data utilization and exploitation to be data-driven.

4.3.2.4 Future expectations on data-drivenness

According to interviewee D, there will be increasingly more fully data-driven enterprises in Europe. However, he perceives that both B2B and B2C companies will face difficulties related to the ownership and privacy of data. In this sense, he feels that companies will need to adapt to new regulations, especially in Europe where laws are stricter than in other countries like US. Moreover, another element that companies will consider is *"where to put data"* both for growing amount and for the consequent issue of security, especially if using the cloud[6]. Finally, he notices that data lakes and tools will be more open-sourced, *"there will be less property of software and solutions".* Thus, technologies, databases used, and their development will be shared to a greater extent.

4.3.3 Organizational change

4.3.3.1 Defining organizational change

Respondent D believes that in general the adoption of BDA is required by competition in the market. In this sense, according to him big data and BDA impacted companies and a sign of this can be observed in two main elements. On one hand, around five years ago many enterprises started to invest in advanced tools. On the other hand, about two years ago a large number started to increasingly hire data scientists. He adds "*this kind of role has been exploding in the last two years".*

[6] "Cloud storage is a way to save data securely online so it can be accessed anytime from any location and easily shared with those who are granted permission" (Investopedia, 2018).

Interviewee D thinks that changes in the context of data-drivenness relate to the establishment of new roles and the acquisition of new technologies. Further, in order to become data-driven, companies often need to modify their mindset to develop the one depicted above (main features). In this sense, culture is perceived as fundamental to be able change and adapt to external environment situations and adopt new technologies such as BDA. He suggests that changes are more difficult for bigger companies *"the bigger you are, the harder it is"* but if employees are "*self-learning and aware that changes will always happen"* than the process is easier.

In the process of becoming more data-driven, respondent D perceives that top management should be aware and support the company but *"the innovation comes from the ground"*. He explains that if there is only an order from the top, the company becomes a *"forced data-driven instead of "innovative data-driven enterprise"* and it will not survive in the long run.

4.3.3.2 Resistance to change

Respondent D deems that depending on the age of company and its innovation and changing culture, some experience resistance to change and others not. It might arise within companies that operate in traditional and conservative industries where competition is stable and they do not face external pressures, thus they are not used to changes.

Data collected from case companies

4.4 TalkPool AB

4.4.1 Big Data and Big Data Analytics

4.4.1.1 Defining Big Data and Big Data Analytics

Respondent E defines big data as huge data sets that, compared to the past, "*have unprecedent speed, variety and volume"*. Similarly, respondent F states that one can speak about big data when information is collected from different sources, thus it is about "*collecting different types of data in order to create more complete information".* Moreover, both respondents agree on the closed link between big data and IoT, considered as its foundation and primary source.

As far as BDA, respondent E describes it as a *"natural result of these kind of data sets"* since companies cannot handle them manually, thus needing computers and technologies to perform this activity. In this perspective, all the interviewees highlight the centrality of AI and machine learning to analyze data and execute predictive analytics "*not only to know what is happening right now but also what will happen in the future".*

4.4.2 Data-drivenness

4.4.2.1 Defining data-drivenness

Both respondents agree on the basic definition of a data-driven company being one that uses data to inform decisions. As far as the explanation of data-drivenness within their company, respondents' opinions correspond since both perceive that at the moment, they are not using big data for their own purposes, thus there are not data-driven in decisions. In fact, according to interviewees the company provides data to its customers through sensors and IoT services, but it does not collect and use that for its own purpose. In this regard, according to respondent E, responsible for marketing and sales, at the moment they do not face the need of collecting and analyzing data for their interest, given the limited the number of clients and business activities. In this regard, he explains that he is not using data as evidence for decisions and that he *"goes more with feel".*

Finally, they both perceive the collection and use of data for TalkPool AB's own purpose and decisions as something viable as the company grows in Sweden. However, respondent F also argues that for TalkPool AB being totally data-driven might be hard given that "*not all decisions points are made by our-selves and we rely on the client for our decisions*".

4.4.2.2 Opportunities of data-drivenness

Both respondents see several opportunities arising from taking decisions driven by data both as far as strategic and operational ones. As far as the former, respondent F believes that "*decisions can be more precise, quicker and you can react to things earlier".* In this perspective, he asserts that they could leverage on big data to drive strategic decisions regarding business development by *"understanding which part of the industry is getting more digitalized, which gaps are present in the market and then address them".* Moreover, interviewee E is confident in the chances provided by big data in decisions on this field. In fact, he remarks the opportunity of obtaining assistance in *"understanding your target groups and how to target them"*. Moreover, the interviewee underlines the possibility to understand where the business is losing customers in order to tackle it and increase sales. Finally, respondent E concludes "*there is a clear opportunity of being data-driven as far as my decisions in marketing are concerned, and sales go hand in hand with it".*

As far as the latter (operational decisions), another opportunity presented refers to the possibility of optimizing processes with automation. Indeed, respondent F states that by collecting data from different sources they could optimize the operations and activities "*that right now only exploit data from silos not combined with data from other sources".*

4.4.2.3 Challenges of data-drivenness

As far the challenges related to data-drivenness, respondents focus on different aspects.

Respondent E highlights cost-related threats such as the cost of time necessary to analyze data as well as the cost of hiring skilled personnel with regard to analytics. As far as the need of hiring skilled employees, respondent F expresses that they are going to face the challenge arising from the need of hiring data scientists as they start collecting and analyze data for their purpose rather than just for clients. Moreover, the cost of analytical technologies needed is perceived by respondent E as an issue depending on the type of technology used.

Respondent F underlines two main challenges concerning the validation and the ownership of data. The first relates to the need to *"make proper evaluation of the data and the model in order to understand and see what kind of decisions you can base on data"*. He states that the initial challenge faced is likely to be the necessity to make assessment on data collected to ensure that *"insights are correct"*. Similarly, respondent E clarifies that trusting insights from data might be challenging and validation is important because *"you can do a lot of things due to data suggestions, but they could still be wrong if you do not understand the context"*. The second refers to the limited possibility to leverage and monetize on clients' data since *"clients have the ownership of data"*.

4.4.2.4 Future expectations on data-drivenness

Respondents share their thoughts about the future of data-drivenness within their company stating that they perceive the likelihood of becoming data-driven as something tangible, also thanks to the support of technologies such as AI. In particular, respondent E suggests that *"in the future, if TalkPool AB will grow, we can start collecting data from other sources for our purpose and analyzing it"* and with the help of AI he believes to decrease his reliance on intuition for taking decisions.

More in detail, respondent E is strongly confident in the future of data-drivenness guided by AI. Considering two different time spans, in a shorter time horizon of 5-10 years he believes that this technology will be useful for analyzing massive amounts of data in a way that decision-makers will have the right data at hand to base their decisions on. In this sense, humans and AI might need to collaborate meaning that *"we as humans cannot do analytics but we can try to perform the logic afterwards"*. On a longer time span of 30 years, he projects that AI will be used to automate several decisions. With respect to the decisions taken by interviewee E, he believes that websites will be automatically changed by AI and that the all marketing strategy is likely to be decided by this technology. He concludes that within this time frame, humans will probably not take some types of strategic decisions that will be, instead, automated.

Another aspect highlighted by interviewee F is the use of prescriptive analytics to guide decisions in the future. In particular, he states that with the evolution of prescriptive analytics decisions will not concern *"black or white situations"* but more options among which decision-makers can choose. In this regard, he perceives that larger organizations will probably benefit more from prescriptive analytics since they might "*combine financial figures with other sources of data and take more complete decisions*".

4.4.3 Organizational change

4.4.3.1 Defining organizational change

Respondents recognize that their organization has been founded in the era of big data and that, since it performs the collection of data for its clients and not for its own objectives, it has not been impacted by this technology. In line with this, respondent F points out that company' operations are not heavily impacted since TalkPool AB is "*more a technology provider*". Respondent E suggests that TalkPool AB will may need to adapt when they will start using big data but *"there will be less shock than in traditional companies such as banks since we are a tech firm"*.

Both interviewees foresee the presence of changes in organization's mindset to become data-driven. Respondent F suggests that both the decision-making process and the support systems to take decisions will change. In fact, he adds that AI and machine learning will act as the basis for decisions, thus changing the decision-making process, more relying on evidences. In this regard, interviewee E concludes stating that *"it will be a process during which intuition and feeling will progressively decrease"*.

Finally, respondent F asserts that the process of change toward data-drivenness will take the form of a *"learning process"* within the company. In this perspective, he explains that even if the company he is leading as a flat hierarchical structure, managers are fundamental to support this process by considering data "*not as a storage cost but as an asset to exploit*" and *"to leave the firm fail and learn"*.

4.4.3.2 Resistance to change

According to respondent F, the change toward data-drivenness in TalkPool AB will partially encounter resistance to change. In fact, given the "*entrepreneurial spirit*" of the company, he believes that people within it are *"willing to change"*. Although, at the same time there are *"strong feelings and emotions"* to consider. In this matter, respondent E thinks that *"the older you are the harder it gets to change"*.

4.5 Ericsson

4.5.1 Big Data and Big Data Analytics

4.5.1.1 Defining Big Data and Big Data Analytics

According to respondent G, big data is about structured, and unstructured sources of data and analytics enables to create structured data out of unstructured information. Moreover, he adds that BDA could be defined as the capability of assemble and make sense of *"ridiculous increasing amount of data"*. In this regard, respondent H clarifies that in general big data does not necessarily entail "massive amounts" but he believes that it is created thanks to *"continuous connection to data sources"*. Both respondents agree that BDA is about analyze data to gather insights thus filtering out what is useful and what is not to inform decisions.

4.5.2 Data-drivenness

4.5.2.1 Defining data-drivenness

The definition of how a data-drivenness can be defined almost correspond in both interviews. In fact, they define it as the use of data from different sources in order to guide and make various kind of decisions. Interviewee H illustrates that usually data used to guide decisions within the company is the one gathered from customers' (telecom operators) networks. However, when decisions are more strategic and pertains to important deals, they take a vaster array of data, also incorporating data trends in the market such as the ones grasped from text analysis and news articles. He says, *"nowadays we are blind if we do not connect different types of data sources to gather relevant insights for decisions"*. According to both, Ericsson can be considered as a data-driven company since it is using data in many different activities to inform decisions and it is growing in that sense.

Indeed, respondent H explains that data are used in two main ways. Firstly, both in R&D and product management to understand how customers are using products and which are the trends in order to identify what the company should develop next. Secondly, in operations big data is used to automate processes. In this regard, respondent G says that Ericsson is using data in configuration, maintenance and fault recovery types of issues which is now being extremely helped by machine learning and algorithm. In addition to that, interviewee G suggests that the networks business area and the analytics team work intensively with big data to make structured data out of unstructured data, making sense of all data collected. Respondent G perceives that some departments are more data-driven than others and that sales, marketing and finance are growing in data-drivenness perspective. For instance, he points out that speculating on a macro-level, forecasts about financial performance in two different countries, might be triggered by external data insights and combined with information from customers.

Interviewee H explains which kind of analytics are used in Ericsson. In particular, he reports that at the moment descriptive analytics are used to understand the current situation getting statistics of the customers, and these are mostly used in sales and product management. Predictive analytics is used especially in operational decisions for predictive maintenance. Prescriptive analytics is about deciding between multiple options and probably they will be better developed in the next future.

According to the respondent G, different branches in Ericsson are investing in AI, machine learning and human skills to be data-driven. In this field, two years ago Ericsson has set up the Global Artificial Intelligence Accelerator (GAIA)[7], creating the machine intelligence that is the union of AI and machine learning. According to the respondent G, the aim is to use this skillset multidisciplinary across different company's areas to serve Ericsson's own operations. In this sense, both interviewees state that various units and departments within the company can have access to the same data lake[8] according to what it is needed and considering the level of sensibility of information. Respondent G states *"collaboration across departments is very important"*.

As far as the mindset of a data-driven company, interviewee G perceives that it relates to people since in general it means that the company incorporates new data-related aspects to the day to day work. Both think that the mindset is important to start trusting insights from data to include them in the decision making. Respondent G adds that when considering data-drivenness, one should consider that it is an iterative process where once that you have discovered something new, you keep looking from something else. Interviewee H believes that Ericsson is characterized by people with two different mindsets. On one hand, there are people that attribute great value in making data available and utilizable for decisions while on the other, there are those who do not believe so much in it.
Moreover, an element of mindset discussed during interviews is intuition. Both believe that being data-driven means also to take decisions by combining personal intuition and evidence from data. With this regard, respondent H provides the example of the role of intuition in innovation. In fact, *"taking fact-based decisions means that you can understand if your intuition is plausible or not"*. He claims the importance of being "*more-fact based in decisions"* by explaining that *"by only being intuitive, people tend to find something that proves their believes and they can be very convincing, but an intuition could be completely wrong"*. In this logic, he perceives that taking into account the evidence from data, decision-makers can understand whether their intuition is right or wrong.

[7] The ultimate goal of GAIA will be to create self-healing, self-organizing and self-configuring autonomous networks. (Ericsson, 2019 b)
[8] A data lake is defined as a deposit of structured and unstructured data in their original form, without classification. Thus, it is less structured than data warehouse (Techopedia, 2019).

4.5.2.2 Opportunities of data-drivenness

Both respondents agree on the fact that gathering insights from data can help decision-makers discover unexpected and unknown factors. That is why data-drivenness is increasingly becoming an integral part of the company. Moreover, interviewee G believes that being data-driven leads to better and faster decisions as well as to money savings. In this line, respondent H believes that being data-driven enables to increase efficiency with automated operations as well as to easier identify problems and better and more efficiently tackle them.

4.5.2.3 Challenges of data-drivenness

According to respondent G possible challenge might arise in case of "over trust on data", thus when a decision-maker relies on the wrong data to base his/her decisions on and it leads to wrong decisions. This is related to a challenge related to data-quality, because in order to exploit data, the company needs to make sure of the quality of data sets. From a different perspective, interviewee H believes that an important challenge faced by a big company as Ericsson relates to the sharing of data across the organization. In fact, there is the need of creating standard tools and procedures to store data and work with it otherwise there could be misunderstandings.

4.5.2.4 Future expectations on data-drivenness

The interviewee G perceives that Ericsson is likely to become more and more data-driven in the future and that all activities will probably be affected. With respect to this, respondent H believes that a key element is to include more prescriptive analytics for strategic decisions. Moreover, the future of data-drivenness depends on mainly two aspects. On one hand, the increasing amount of data from new and various sources that the company is going to have at its disposal. On the other hand, the quality of data sets that it can access. In this sense, *"the better quality of data, the better outcome it will be".*

Furthermore, in terms of technologies, interviewee G thinks that AI will improve but knowing right now how it will change is almost impossible. He provides a further explanation by considering that less than 10 years ago many things that we have right now, were not imaginable. However, he also states that it is possible to see some patterns of developments, especially about the automation with AI and the re-thinking of some processes. Probably, with AI some jobs will be replaced but others will be created at the same time. Furthermore, in terms of how data-driven decisions will be, the decision support that decision-makers will get with growing amount of data will evolve year by year.

4.5.3 Organizational change

4.5.3.1 Defining organizational change

Respondent G points out that in Ericsson digitalization has impacted on all aspects of the business *"from how people conduct the work with the new tools that they can use, to how they can work in a* *smarter way".* As far as analytics, both respondents state that Ericsson faced the need to hire skilled people in this field such as software developers. In this sense, interviewee G believes that Ericsson is following a sort of adaptation process to digitalization, new technologies and the increasing amount of data and that it will keep going exponentially as the external environment will evolve. In this perspective, both representatives perceive that if a company is not able to adapt to the external environment, it risks being out of the market and lose competitiveness.

Respondent H states, *"going into data-drivenness is a huge change management task"* and change relates to how data is valued within the company. He also clarifies that in Ericsson this change is undergoing. In an akin line of argument, interviewee G perceives that becoming and being data-driven entails changes, provoked by the need of heavily invest in tools, systems and human skills. Moreover, the changes within a big company like Ericsson happen in diverse ways and different departments will deal with change differently. In some functions it might be seen as more obvious to be driven by data while in others it is still be seen as something too far. Thus, being an adaptation process of change to become completely data-driven, the entire organization is not moving at the same pace.

In the adaptation process that Ericsson is undergoing in terms of data-drivenness, the respondent G perceives that people will need to adapt in the way they are working, and this will be a gradual process, meaning that there will be progressively a new modus operandi. In this sense, he adds that *"change does not happen by using post-it on the wall"* but by starting using different methodologies and tools that, if turn to be useful, will change the mindset of the company. Furthermore, he believes that an important element in the process of change is what he defines with "creativity" because it entails curiosity and the ability of re-think how activities are performed. Data might suggest to the company in which direction to go, but then the enterprise has to acquire these insights with creativity. In the process of becoming more and more data-driven, the role of the top management is perceived as being extremely important because it leads the decisions about investments in both technologies and people. In this regard, interviewee H believes that there is a mix of bottom-up and top-down approach and he defines it as a *"bottom-up journey".* To clarify this statement, he explains that lower level employees perceive the need to be more data-driven but top-management is entitled to make investment decisions about technologies and hiring people. To provide an example he adds that, back to two years ago, the innovation garage in Ericsson performed a sort of leading role in guiding the company toward the importance of valuing data. However, at that moment, there was a lack of analytical competences especially in AI and they started to involve employees interested in the topic as well as some managers. He concludes that probably thanks to this initiative, higher level employees acquired awareness of the importance of investing in this field.

4.5.3.2 Resistance to change

According to respondent H, the fact that with data the value of intuition is lowered could be a source of resistance to change because people might be scared of proves showing that they are wrong. Respondent G believes that people in Ericsson are open to change but, at the same time, change could also be perceived as threatening. For instance, the automation could be considered as a threat because some manual jobs will be replaced in order to achieve efficiency. At the same time, employees also need to learn to perform their job with new technologies and this could entail some sort of resistance to change if people perceive it as a menace. On the other hand, if employees within the organization, appreciate more the opportunities of new technologies and data-drivenness rather than the threats, they will might be open to change since their activities will be enhanced.

4.6 GothNet

4.6.1 Big Data and Big Data Analytics

4.6.1.1 Defining Big Data and Big Data Analytics

According to respondent I, big data "*is a megatrend*" and one can speak about it when "*data is taken from various systems and sources and then analyzed in order to enhance the information*". Moreover, both respondents point out that the amount of data that GothNet is dealing with nowadays is bigger than before, but it cannot be measured in terms of terabytes every day. In this sense, respondent L says, *"we are not dealing with big data as it is generally considered".*

4.6.2 Data-drivenness

4.6.2.1 Defining data-drivenness

Interviewee L believes that a company is data-driven when it uses data to inform decisions, evaluate or find business opportunities *"such as where to put new facilities".* Both respondents agree that GothNet as always dealt with data but now it is bigger in amount and better analyzed thanks to more advanced tools. In this perspective, they believe that GothNet *"has started to be data-driven"* in the last two years, thanks to some investments in analytics and data visualization tools. In detail, given his position in the company, interviewee L explains that GothNet collects large amount of data in its Network Inventory System[9], that than is analyzed and shared with other functions and departments, marketing in particular. Respondent I states that, in general, big data can be used in mainly two ways. On one hand, it can be used to find new innovation avenues such as new services or new businesses,

[9] Network Inventory System is a geographic inventory system for the fiber network which contains information about the deployment and the assets (Odgren Lundh, P., personal communication, 2019).

on the other hand data can be used in order to optimize the current business making customers more satisfied. In this perspective, he believes that the "*firm engages in the second type of use, meaning that GothNet is actually exploiting data for improving current businesses*". In particular, he adds that the company is trying to data-driven to automate the services sale process for customers in order to improve it and that it is data-driven on automated pricing models by combining different data sources. In fact, respondent L clarifies that they are using internal data combined with external geographical data (such as addresses) collected through Metria[10]. In this view, as far as his role as business developer, respondent I believes that he can explore the market by, for instance, correlating the data from operator companies' addresses and from the presence/lack of fibers. He also adds *"the better data we have in the Network Inventory System, the better correlations we can make"*.

Culture is considered as a key element to be data-driven by interviewee L, but he perceives that *"the right mindset is not already in place"* in GothNet because not all employees share it, so he refers to a need of changing it in this light. Respondent I perceives that "openness" is a key ingredient to be more data-driven. With this term he means that people within GothNet should be able to share data and be open to it. Also, he believes that there should be a "*common understanding on why we are doing this".* In this perspective, interviewee I states that the company *"is made of people from different backgrounds, skills and education"* that should understand the way data can be used and how it can worth for the company.

The sharing of data expressed by respondent I relates to the accessibility of data across the company and he suggests that within GothNet especially two departments share data: network and marketing and sales. In this light, according to respondent L, anyone in GothNet can have access to data by asking him for information since he is entitled for this. In this sense, interviewee L perceives that there is sharing of data and collaboration among functions.

As far as the role of intuition, according to respondent L, decisions are now more fact-based meaning that decision-makers can consider market and business development opportunities based on insights from data rather than only on their intuition. In this perspective, their intuitions might be proven or informed by data.

4.6.2.2 Opportunities of data-drivenness

Respondents' opinions about opportunities mostly overlap. In particular, both believe that one opportunity of being data-driven is to improve productivity and efficiency. Respondent I explains,

[10] Metria is a leading supplier of digital map services, measurement, GIS and remote sensing (Metria, 2019).

"*doing more with less people".* The second opportunity refers to the possibility of increase customer satisfaction, providing better offerings. Moreover, interviewee I believes that if the data quality challenge is overcome, data-driven decisions could be better. Overall, both think that the biggest opportunity as well as the goal of being data-driven is to improve the position of GothNet in the market, attracting more customers.

4.6.2.3 Challenges of data-drivenness

Respondent I perceives that one important challenge pertains to data-quality. In fact, when taking decisions, one should make sure that the quality of data is accurate. He explains that the company is putting effort on ensuring and verify the quality of data collected, by grouping data using visualization tools. In this perspective, interviewee L points out that since internal data is created by project department, a challenge relates to make sure that it is well-documented otherwise decisions based on that data turn to be incorrect. In this line, he concludes that *"the main challenge relates to human errors".*

Moreover, another challenge faced by GothNet relates to the exchange of data with customers meaning that *"there should be a common understanding on how the exchange of data should be done".* Another challenge lies in the need of hiring skilled employees in analytics that can support the company in being more data-driven. Respondent I clarifies that it is an issue to the extent that the management does not perceive this as something necessary, thus it is not highly investing on it. In addition, respondent L states that the challenge is the presence of some resistance to change among employees.

4.6.2.4 Future expectations on data-drivenness

As far as the future of data-drivenness in GothNet, respondent I tells that they are now working on IoT and that by connecting everything more data will be generated and collected. This will lead to the need of more analytics skills to base more decisions on data. Moreover, he shares opinions on how his role as business developer will evolve. In this regard, he believes that improving data correlation and analytics, it could improve as well. He defines itself as optimistic in terms of becoming more and more data-driven, even if they work with business customers. He adds that *"right now we have started step by step*" and that as data analytics improves within GothNet, data-drivenness will evolve, too. Similarly, according to respondent L, GothNet will become gradually more data-driven especially in operational decisions as well as business development ones in the Gothenburg region as the city expands. Finally, he states that the future of data-drivenness in GothNet will principally involve automated decisions rather than strategic ones.

4.6.3 Organizational change

4.6.3.1 Defining organizational change

According to interviewee I, GothNet faced the need to adapt to digitalization and BDA, in particular as "*reaction to what their competitors where doing in terms of process automation".* Indeed, once that the company started dealing with BDA around two years ago, it faces the need of hire people with the right education like data analysts. Notwithstanding this need, he states that they are not intensively hiring in that field and that they have essentially one person working on it (that is respondent L). Moreover, both interviewees explain that the creation of more data, led them to invest in a new Network Inventory System with more capabilities. Moreover, respondent L perceives that his role as system engineer is evolving as GothNet is evolving in the light of analytics, too.

Respondent I perceives that becoming data-driven entails several changes guided by the necessity of adaptation faced by the company. In fact, he clarifies that since they *"are working in a market that is growing*", GothNet needs to change in line with the market. In this context, respondent L clarifies the role played by company' mindset that should change. In fact, he perceives that change is a matter of modifying culture, *"change the old habits".* In particular, he believes that they should be more *"entrepreneurs, open-minded and being able to have a broader view on the opportunities coming from being data-driven".* In that sense he perceives that the mindset should let employees consider data as valuable rather than as cost. Moreover, to increase the level of data-drivenness, respondent I identifies the need of investing in analytics technologies and human skills.

According to both respondents, the process of becoming more data-driven follows a bottom-up approach where employees are convinced of the opportunities coming from data-drivenness. However, they partially disagree about the role played by top management in this process. Respondent I believes that *"top-management does not perceive it (data-drivenness) as much important"* while interviewee L states that it is supporting the company *"with investments and risk-taking activities"*, related to be more data-driven. For instance, according to respondent L, the utilization of automated pricing model entails some risks that the top management is allowing to take because of a long-term benefit expectation.

4.6.3.2 Resistance to change

According to respondent I, being GothNet a small company, changes happen relatively easily and resistance to change is something that he does not perceive. On the contrary, according to respondent L, there is some resistance to change in the process of including more data in decisions. In detail, the reasons could be that some employees fear to lose their job or to change their way of working they are used to; that they might do not trust data in terms of supporting tool and finally that the role of intuition in decisions changes.

4.7 Telia Carrier

4.7.1 Big Data and Big Data Analytics

4.7.1.1 Defining Big Data and Big Data Analytics

According to respondent M, big data can be seen as a "*buzzword*". It is not something new, but the technologies used in order to analyze it improved over time, enabling to handle larger data sets compared to the past.

4.7.2 Data-drivenness

4.7.2.1 Defining data-drivenness

Respondent M defines a data-driven company as one that combines *"knowledge and intellect of humans with data available and analyzed".* In addition, he points out that being data-driven does not mean to be dominated by data. Interviewee M believes that big data and BDA are, to some extent, embedded in daily activities of Telia Carrier as they are *"increasingly characterizing its DNA".* As far as data-drivenness within Telia Carrier, the respondent says, *"we are on the way to become because you can never be totally satisfied"* as data usage is done *"at different degrees"* and in different business areas that are more data-driven than others. In particular, he explains that the company collects huge amount of data from networks that they are operating and "*in order to fulfill our services toward customers*" they need to make use of that data. In relation to network department, respondent M states that it is quite data-driven since they also have a network operating center operating 24/7 being highly automated. Moreover, interviewee M clarifies that data is used both for financial analysis to understand the business and in marketing department that is increasingly becoming data-driven also exploiting external data from social media channels like LinkedIn. With this regard, interviewee explains that *"Telia Carrier operates in a commoditize industry"* and in order to position the company in the industry, the marketing department intensively exploits social media.
To further explicate how analytics are performed in Telia Carrier, respondent M tells that each department analyzes data according to its own need, working in cooperation with the IT department.
As far as the mindset, respondent M re-calls his consideration of big data usage within the DNA of the company explaining that the mindset enables people to embed insights from data into day to day decisions combined with their own experiences. In this respect, intuition is something that is combined with data in order to investigate whether that gut feeling should be chased or not.
According to him, an important element of the mindset relates to a working environment where people have less administrative tasks to perform and more time to reflect on what to do with data

insights. In this context, he perceives that more flexible schedules and team-works are key ingredients.

Considering the accessibility of data within Telia Carrier, interviewee M explains that data are not stored in silos but instead they are collected in data lakes, in traditional data warehouses and in platforms and they are accessible by different departments that then carry out the analysis.

4.7.2.2 Opportunities of data-drivenness

Interviewee M believes that being data-driven enables to take *"more informed and trustworthy decisions"*. Furthermore, according to respondent M, the final opportunity of being data-driven is that customers are more satisfied because a data-driven company is highly reliable. Also, given the activity performed by Telia Carrier in the telecommunication sector, the local community benefits from the company relying on data for decisions.

4.7.2.3 Challenges of data-drivenness

The main challenges that the respondent highlights pertain to "*time, money and skills*". In particular, time is perceived as a requirement for an evolutionary process as the one that Telia Carrier is pursuing. Money relates to the need of make investments in technologies and people that represent the last challenge faced. In fact, according to interviewee M, skilled people in coding and analytics are key for data-drivenness because without having that capabilities, data does not acquire sense. Furthermore, providing this example *"you might have a computer nerd and a sales guy, and they don't understand each other",* he states that the lack of communication skills might be a challenge.

4.7.2.4 Future expectations on data-drivenness

According to respondent M, Telia Carrier will be characterized by an increasing level of data-drivenness. More in particular, he perceives that more AI and robotics will be used in this context but, at the same time, *"a lot of human interaction will be present"*.

4.7.3 Organizational change

4.7.3.1 Defining organizational change

Respondent M describes the impact of creation of big data on Telia Carrier as a loop. In fact, on one hand *"with the growth of data our business grows because we are the ones carrying data as service"*. On the other hand, the creation of more data *"enables us to incorporate it to run the business".* Moreover, he points out that the *"level of granularity"* has increased over time so the need of state-of-the-art analytics has grown, too. In this light, interviewee M lightens the fairly recent rearrangement of the IT department now called "IT and engineering department" where data-scientists have been added as well as the occasional support of external companies' experts in analytics.

At the same time, interviewee does not perceive the adoption of advanced analytics as an external pressure to adapt but rather as an influence that the company receives from the environment. He concludes stating "*we drive things, but we are also influenced by what is happening in the world".* According to the respondent, becoming data-driven entails *"cultural change and it takes time to change it"*. In describing what he means with cultural change, respondent M states that the mindset of employees changes since the working environment changes, too. He describes it as an *"evolutionary journey"* to achieve the target of being data-driven and maintain a relevant position in the sector.

In becoming more and more data-driven, interviewee M perceives that the role of top-management is important as it establishes the vision that the company follows. However, he states that the push for data-drivenness comes from the bottom since employees ask for it. He describes this as a *"synchronize"* process.

4.7.3.2 Resistance to change

Respondent M thinks that there could be resistance to change due to fear of losing or changing current jobs and of decreasing in power.

Table 5: Summary of data collection

	Big Data and Big Data Analytics	Data-Drivenness				Organizational change	
	Defining Big Data and BDA	**Defining data-drivenness**	**Opportunities**	**Challenges**	**Future expectations**	**Defining organizational change**	**Resistance to change**
Senior manager innovation and digital services (respondent A)	Way of discovering new factors; relation with digitalization	Use data as asset; data-driven decisions; sharing of data; combination of data sources	Better, more accurate decisions; innovation; understand customers for targeting	Privacy; handling big data; need capabilities; data reliability	Entire society affected by data; data-drivenness prerequisite to survive	BDA adoption to remain competitive; culture enables adaptation; top management support BUT bottom push	Fear of changing roles & adaptation to new rules and processes
Meltwater representatives (respondents B/C)	Internal data + external data; size of company; BDA with technologies	Decisions on data and real-time info; data sources combination; intuition decrease; collaboration; B2B & B2C, small & big companies	Better targeted decisions; forecast development; product development; gain competitive advantage	Privacy; lack of trust in data insights	Creation of new analytical technologies; more use of external data	Adaptation to digitalization, big data and BDA; gradual change; investments; top management skeptical	Inexperience and uncertainty & fear of new working styles
Technology executive IBM (respondent D)	Structured + unstructured data; BDA for insights; B2B and B2C	Get advantage from data; strategic & operational; experience + data; skilled people & infrastructure; open-mindset; data sharing	More specific and precise decisions; better targeting; business development	Lack of capabilities; Data trustworthiness; compliance to country legislation	More data-driven EU enterprises; stricter privacy regulations; open sourced tools	Adoption of BDA required by competition; new roles; new technologies; change mindset; top management support BUT ground push	Depends on firm' age & innovation and changing culture & type of industry
TalkPool AB (respondents E/F)	Speed, variety & volume; IoT; BDA natural result (AI+ machine learning)	Use data to inform decision; not data-driven	Precise, quicker & reactive decisions; optimization with automation	Cost of time and hiring; need data validation	Likelihood to become data-driven; increase use of AI	No huge impact; will be a learning process with changes in mindset	Won't be present -- → entrepreneurial spirit
Ericsson (respondents G/H)	Structured + unstructured data; continuous connection to sources; BDA make sense of data	Combination data sources to guide decisions; investments in technologies and people; data sharing; collaboration; intuition check; daily data incorporation; data-driven in strategy and operations	Better & faster decisions; innovation; increase efficiency with automation	Need data quality validation; need of standards to share data in organization	Become more and more data-driven; use of AI and prescriptive analytics; more data & better quality	Huge impact of digitalization; adaptation to survive; change management task with investments in tools and people, new procedures & mindset; top management decision BUT bottom up push	Less reliance on intuition; job replacement; need to learn
GothNet (respondents I/L)	Various sources; analysis to inform decisions; size of company	Use data to inform decisions; sharing & collaboration; combination data sources; data-driven operational decisions	Improve productivity & efficiency; increase customer satisfaction; improve company' position	Data quality check; documentation of data; hiring; resistance to change	Become more data-driven in operational automated decisions	Adaptation as reaction to competition; cultural changes & investments in people and tools; top management decide BUT bottom up process	Relatively easy changes; fear of lose job & changing procedures; change intuition role
Telia Carrier (respondent M)	Buzzword; technologies new for larger data sets	Knowledge + data; combination data; data sharing; daily data use; flexible working environment; human skills; data-driven in strategy and operations	More informed & reliable decisions; increase customer satisfaction; benefit local community	Time requirement; money for investments; lack communication skills	Increase in data-drivenness; AI and robotics with human interaction	Adoption of BDA for external influence; change working environment & culture; hiring and rearrangements; synchronize process top-bottom	Worry of losing job; change current position; decrease power

5. Data analysis

In this chapter data analysis will be presented. It includes the comparison between theoretical findings and empirical findings from experts and case companies' representatives as well as comparison across cases. In order to deeply analyze the findings, the author carries out some critical thinking. The categories of analysis are the same used to present empirical findings: (1) Big data and Big Data Analytics, (2) Data-drivenness and (3) Organizational change and the same equality is valid for sub-categories. Patterns of analysis are defined based upon the main points expressed by the interviewees. Moreover, when empirical findings are collected on aspects not present in theory, the author will conduct a comparison across data collected from primary sources.

Finally, at the end of each category, the author reports a summary table aimed at supporting and streamlining the reading process of data analysis.

5.1 Big Data and Big Data Analytics

5.1.1 Defining Big Data and Big Data Analytics

Both experts and representatives of case companies provide various definitions of big data being in line with Hartmann, et al. (2014) who suggests that, although this concept is widely discussed, a unique definition does not exist. Moreover, big data might be associated with different elements depending on companies' activities (Blackburn, et al., 2017) and a specific threshold to identify what is big data does not exist since it varies across size, sector and location of enterprises (Haider & Gandomi, 2015). For instance, respondents from GothNet point out that their company is not dealing with terabytes of data per day and with big data as generally considered. That is probably because of the small size of the municipal company and its presence on a circumscribed geographical area. This argument conforms with what experts from Meltwater suggest by stating that the amount of data that a company collects is relative to its size.

Another perspective is provided by expert A, who suggests that drawing the line between big data and normal data is very complex because *"some dimensions changed compared to the past".* This consideration seems to be in accordance with Haider and Gandomi (2015) who state that dimensions change over time as technologies for storing, handling and analyzing data evolve, too.

In defining big data, the majority of respondents highlights that it is created by the presence of various kind of data sources. This can be associated with what theory calls "variety" dimension that is defined as the heterogeneity found in data (George, et al., 2016) and as the diversity in data sets (Haider & Gandomi, 2015). Respondent F from TalkPool AB and respondent I from GothNet simply explain that big data is information collected from different sources. More in detail, expert D from IBM and respondent G from Ericsson express variety concept referring to the combination of structured and unstructured data while experts from Meltwater describe it as the mix of internal and external data sources, as also suggested by respondent D from IBM. Moreover, respondent E from TalkPool AB provides a definition that is pretty similar to the one given by Davis (2014, p.41) as he defines big data as huge data sets with unprecedent speed, variety and volume. This definition seems also to be very closed to the non-academic definitions of Gartner IT Glossary (2019) and TechAmerica Foundation's Federal Big Data Commission (2012), presented in the literature review chapter.

Another aspect emerged from some respondents is the relation between big data, digitalization and digital technologies that the researcher found in the literature review, too. In fact, similarly to Pereira, et al. (2018), expert A believes that in a more digitalized world where devices are connected, higher amount of data of various type is generated. In addition, being TalkPool AB a provider of IoT services, both its representatives highlight the close link between IoT and big data since the former is the primary source of big data, as explained by Chen, et al. (2014). Likewise, respondent H from Ericsson points out that the adjective "big" entails a growing amount that is permitted by *"continuous connection to data sources"*, thanks to the use of digital tools.

What is noticeable from empirical findings is that some other respondents focus on the more technical aspect of big data as the researcher observed also in the literature review. In fact, expert A, respondent I from GothNet and respondent M from Telia Carrier, point out that what defines big data is the use of technologies necessary to handle it in order to enhance information and exploit it. This could be linked with Bharadwaj, et al (2013) explanation of volume being higher than the ability of common processing devices of collecting and managing data.

As far as BDA, almost all respondents agree in stating that it consists of technologies used in order to handle data and extract valuable insights from it as pointed out by Chen, et al. (2012); Wamba, et al. (2015); Curry (2016) and Blackburn, et al. (2017). A remarkable aspect that the researcher did not explicitly found in theory is that both B2C and B2B companies are using BDA in order to combine different types of data to gather insights. This goal of BDA is also reported by both respondents from Ericsson and GothNet who explain that it is used in order to analyze and make sense of (huge amount of) data with the aim of obtaining useful insights to inform decisions. In this perspective, expert A explains that analysis of data enables to find and discover new elements and create new types of services. Respondents G, H, I, L and A perspectives seem to coincide with Curry (2016) who suggests

that analysis phase in the big data value chain is the process during which organizations explore and model data in order to find out the most relevant information for their purposes.
Moreover, like Chen, et al. (2012) state that the term BDA was coined as a consequence of the creation of more and diverse data to handle, respondent E from TalkPool AB perceives that BDA is a natural result of these new kind of data sets because companies cannot handle them manually. Focusing on technologies used to perform analytics, expert C from Meltwater explains that BDA is the analysis of data using a vast array of diverse technologies depending on the typologies of data and what the company needs or want to find. Following a similar argument on technologies, TalkPool AB representatives mention the centrality of AI and machine learning to analyze data and execute predictive analytics that allow to predict what will happen in the future, as explained by Blackburn, et al. (2017).

To recap the analysis of category (1) Big Data and Big Data Analytics, it appears that a unique definition of big data does not exist as respondents focus on various aspects analyzed in the light literature review. However, examining their understanding of both big data and BDA is essential to address the research questions in order to avoid wrong comparison across cases. In fact, they are at the basis of data-drivenness.
Hence, the following table shades the lights on the main aspects that support the author in answering the main research question.
For the purpose of precision, it should be remarked that in tables the absence of many disagreements (X) across findings might be explained by the fact that case companies are all B2B pertaining to the same sector and that the presence of agreement (✓) does not necessarily mean that all companies are acting in the same way, as detailly explained during the analysis. Furthermore, it might be that theory highlights something expressed also by respondents but with differences not explicable in a table.

Table 6: Summary of data analysis (category 1)

	Big Data and Big Data Analytics				
	Defining Big Data and Big Data Analytics				
	Amount depending on company size	**Various data sources**	**Relation with digitalization**	**Technical aspect of big data**	**BDA to make sense of data**
Senior manager innovation and digital services (respondent A)	-	-	✓	✓	✓
Meltwater representatives (respondents B/C)	✓	✓	-	-	-
Technology executive IBM (respondent D)	-	✓	-	-	✓
TalkPool AB (respondents E/F)	-	✓	✓	-	-
Ericsson (respondents G/H)	-	✓	✓	-	✓
GothNet (respondents I/L)	✓	✓	-	✓	✓
Telia Carrier (respondent M)	-	-	-	✓	-
Theory	✓	✓	✓	✓	✓

Legend: the table shows the main paths upon which respondents and theory either agree (✓), disagree (X) or did not explicitly utter (-)[11].

[11] If the title in the table has a /, then the symbols in the respective cell will be two. The former referring to the words before the slash and the second referring to the ones after.

5.2 Data-drivenness

5.2.1 Defining data-drivenness

As explained in the introduction, the aim of this study is to explore how companies are dealing with data-drivenness and a fundamental step, after having considered their understanding of big data and BDA, is to analyze how they define the concept and which are the key characteristics within case companies. In the literature review, the main elements of data-drivenness have been presented in three distinct categories: tangible resource, intangible resources and human skills. In the empirical findings, notwithstanding the fact they are all B2B companies in the telecommunication sector and that their definitions mostly coincide with the ones provided in the literature review, the elements are considered to different extents by them given each specific context and without a net separation. Moreover, also experts explained it from some diverse perspectives.

To start with, the definitions of data-driven companies provided by respondents B and C from Meltwater, E and F from TalkPool AB, G and H from Ericsson and L from GothNet coincide with theoretical definitions, describing them as companies able to convert data into insights that are used to inform decisions (Anderson, 2015; Deloitte 2016; Mikalef, et al., 2018; Accenture Labs, 2018). This decisional activity is linked with the big data usage phase of the value chain during which companies use previously analyzed data to take informed decisions (Miller & Mork, 2013; Curry, 2016). From a slightly different perspective, experts A and D define a data-driven enterprise as one that exploits data to gain value and advantage, by considering data as an asset. Another interpretation, perfectly in line with the one expressed by Anderson (2015), is given by respondent M from Telia Carrier, who suggests that data-drivenness entails the combination of knowledge and expertise of decision-makers with insights from data, as being data-driven does not mean to let data doing or deciding everything. To be honest, also expert D from IBM highlights the importance of that combination to effectively be data-driven.

Despite the fact that all case companies provide their definition of the topic, data-drivenness is implemented differently within each company, as reported by their representatives. For instance, TalkPool AB is not data-driven. In fact, in line with what Mikalef, et al (2018) point out, the prerequisite to be data-driven is to collect data and TalkPool AB is not doing that for its own purposes. Recalling what its representatives explain, the company has so little clients and business activities that collecting and analyzing data is not worth it. That is also the reason why TalkPool AB' respondents do not share other believes about the use of big data and data-drivenness within their company. On the contrary, both Ericsson and Telia Carrier define themselves as being characterized by data-drivenness both in many operational and strategic decisions, pointing out that some departments and functions are more data-driven than others. That could be because they are bigger in size and more structured compared to GothNet, that instead, perceive to be data-driven only as far as automated operational decisions are concerned. This element of difference was not explicitly found in the literature review, where a clear difference between typology of decisions in terms of data-drivenness was not expressed. However, also expert D from IBM clarifies that it relates to both typologies of decisions.

An interesting element typifying data-driven enterprises highlighted by experts and some representatives of case companies concerns the ability to combine different sources of data, especially external and internal, in order to take more informed decisions. This appears to be related to the variety dimension addressed in the previous section of analysis concerning big data and BDA. In particular, expert A and respondent H from Ericsson believe that companies usually couple internal data of the company with external data from market trends to guide strategic decisions. Respondents from Meltwater suggest that enterprises should do that regardless because collecting data is not enough. In addition to that, they also provide a specification suitable with the context discussed in this research. In fact, according to them, smaller companies in the telecommunication sector might combine external data from locations while bigger companies might use external data from social media and editorials. Suffice it to say that interviewee I from GothNet explains that they exploit external geographical data (locations) whereas respondents from Ericsson and Telia Carrier confirm what Meltwater suggests.

Two further macro-aspects of data-drivenness considered by the majority of respondents concern collaboration within the organization (Anderson, 2015) as well as accessibility and sharing of data across departments, theoretically addressed by Anderson (2015) and Patil and Mason (2015).
As far as the former, respondents from Ericsson stress the importance of collaboration across departments that Telia Carrier’s representative describes with team-working environment. Similarly, experts from Meltwater remark the essentiality of shared communication between analytical and decision-making part of companies. In this regard, respondent L believes that in GothNet there is a strong collaboration of functions with the analytical one, that is performed mainly by him.
The latter aspect is addressed by Ericsson, GothNet and Telia Carrier, that regardless of their specific characteristics, explain that data is, to some extent and with some challenges, sharable by different parts within their organizations, based on the precise needs. This seems to match with the theoretical concept of “democratization of data” (Patil & Mason, 2015). However, it seems that this element is

highly dependent on company' size. In smaller companies, such as GothNet, collaboration and data sharing are easier to establish since there could be a direct contact between analytical personnel and decision-makers. On the contrary, in bigger companies like Ericsson and Telia Carrier this could be challenging and risky given the unfeasibility of an immediate interaction between all the parties involved as well as the requirement of tools for sharing data across departments. In particular, as explained by expert A indicates that sharing of data within big companies might be dangerous due to risk of manipulation.

Culture has been considered as key for being a data-driven enterprise (Anderson, 2015; Mikalef, et al., 2018) and it is largely discussed in the literature review as part of intangible elements. Not surprisingly, all respondents, except the ones from TalkPool AB, shared their opinion around the mindset of such company. In detail, respondent G from Ericsson and respondent M from Telia Carrier, agree on the idea that the mindset leads company to embed data-related aspects and insights into day-to-day activities in their companies, in accordance with Pigni, et al. (2016) and Deloitte (2018). In this logic, respondents from Ericsson add that being able to trust data insights is fundamental, matching Trieu, et al. (2018) description of a "fact-based decision-making culture". However, interviewee H from Ericsson explains that employees have different mindsets because some recognize the value of data while others not yet. This coincides with the perception of respondent L about GothNet, who perceives that in his company a common data-driven culture is not yet in place. That is probably caused by the fact that culture is a broad and complicated topic.
Lastly, in line with what explained by McAfee and Brynjolfsson (2012), the majority of respondents agree on the fact that data-drivenness convey companies to reduce the role played by intuition since it is coupled with insights from data. In addition to that, respondent H from Ericsson, respondent L from GothNet and interviewee M from Telia Carrier, share similar opinions concerning the role played by evidence from data that enables to prove or disprove decision-makers' gut feeling. This seems to correspond with the absence of "instinct-based veto" suggested by Berndtsson, et al. (2018).

Finally, the last but not least element considered as constituting data-driven organizations concerns the presence of technologies and human skills enhancing data-drivenness implementation. As far as human skills are concerned, companies reveal that they needed to hire skillful employees in the field of analytics such as data-scientists in order to start being data-driven. For the purpose of clarity, two explications are needed. Firstly, the level of hiring within case companies is diverse presumably due to their difference in size that might affects their investment capacity. Secondly, companies probably have a number of skilled employees in analytics relative to the overall number of workers. These two

clarifications are suitable to explain why Ericsson and Telia Carrier are intensively hiring data scientists whereas GothNet has few people working at analytics.
Moreover, in line with what theory suggests (Ottanio, 2014; Mikalef, et al., 2018), IBM's expert identifies the essentiality of having skilled people in analytics and infrastructure and architecture of data sources. An intriguing consideration provided by respondent D is that companies started to invest in data and analytical technologies around 5 years ago and some years later also in skilled employees. As a matter of fact, both Ericsson and GothNet argue that their company invested in advanced technologies approximately 2 years ago, respectively in AI and visualization tools. Just to be specific, given is position in GothNet, respondent L explains the importance of having invested in visualization technologies as also expressed by Seddon and Currie (2017), in order to exploit value from data.

5.2.2 Opportunities of data-drivenness

In the literature review, the author reported the main general opportunities arising from being data-driven, as they might vary across sector and company activity. To be honest, in the context of this research the findings collected from experts and case companies' representatives mostly coincide among each other and also with theory, probably because companies pertain to the same sector even if performing different tasks. What is more, opportunities highlighted during interviewees seem to be a mix of the ones related to big data and BDA and to data-drivenness. That presumably is the result of big data and BDA being at the foundation of data-drivenness. In particular, the author identifies some main shared opportunities that are outlined below.

Firstly, in correspondence with McAfee and Brynjolfsson (2012), Economist Intelligence Unit (2012) and Mikalef, et al. (2018), almost all respondents agree that data-driven decisions are better, more accurate and precise. This could appear to be easily predictable and foreseen, but it is probably at the basis of company's choice to become data-driven. For instance, this is deeply addressed by TalkPool AB' respondents who seem to bet on this opportunity in considering the possibility of becoming data-driven. In addition, the majority of interviewees believes that the likelihood of having enhanced decisions applies to strategic ones such as targeting and business development as well as operational ones thanks to automation that increases efficiency. This last element is considered by Fitzgerald, et al. (2013), Halaweh and Massry (2015), Lee (2017) and Parviainen, et al. (2017) as an opportunity of applying BDA to streamline operations and improve business processes.

Secondly, according to the majority of respondents, thanks to data insights companies are able to discover new innovation avenues, being capable of following customers' needs and market trends. The possibility of identifying and discovering unknown paths has been theoretically addressed in relation to opportunities of big data and BDA (Halaweh & Massry, 2015; Lee, 2017; Blackburn, et al., 2017). In addition, experts from Meltwater perfectly agree with Sokolowski (2018) in stating that combining different data sources insights, enterprises are able to catch signals from competitors and market trends, essential for forecast development. This opportunity is perceived by some respondents as providing the overall chance of gain competitive advantage in line with Schroeck, et al. (2012) and EY (2014). Indeed, for instance, the possibility of improving customer satisfaction is seen as critical element to improve the position of GothNet in the market. From a slightly different perspective, respondent M from Telia Carrier perceives that a data-driven company is more reliable and given its activity in the telecommunication sector, the overall opportunity is to benefit the local community.

5.2.3 Challenges of data-drivenness

As for opportunities, in the literature review the researcher presented some generally accepted challenges, that were divided into data-related and culture-related issues. From empirical findings, the majority of challenges belongs to the first category and, in particular, to data-quality and privacy issues. Hence, challenges pertaining to excess value of intuition and the lack of accountability outlined by theory, have not been expressed by respondents.

As far as data-quality is concerned, the majority of interviewees highlight the need of verifying the quality of data before basing decisions on it. Anderson (2015) suggests that due to skepticism on data quality companies are increasingly trying to check its reliability and Deloitte (2018) presents it as a serious issue. Moreover, controlling data-quality is part of the curation phase along the big data value chain and it becomes essential especially when the number of data generation sources increases (Demchenko, et al., 2013; Curry, 2016; Curry & Freitas, 2016). In fact, as suggested by experts A and D, data might be manipulated and if a company does not recognize it, data-driven decisions could be wrong, as suggested by Janssen, et al. (2017). Moreover, Meltwater experts' idea that the lack of trust in data insights prevents some companies to base more decisions on data might resemble the skepticism caused by quality concerns highlighted by Anderson (2015).

Privacy related challenges are considered from two different perspectives by theory and empirical findings. On one hand, Halaweh and Massry (2015) seem to bring customers' point of view stating that for companies might be difficult to maintain acceptable privacy level as often they exploit individuals' information without their consensus. On the other hand, the perspective taken by respondents, seems to be the one of companies that, due to restrictive privacy legislations such as GDPR, might face the challenge of having less data at their disposal. What is to be noticed is that in interviews only experts highlight this issue. This could be due to the fact that being companies considered in the research B2B, they might not observe it as challenging, yet. For instance, another element presented by expert D from IBM is that multinational corporations might face the challenge of complying with different privacy legislations that are country specific. However, this has not being pointed out by neither Ericsson nor Telia Carrier which operates in several nations.

Moreover, besides data-quality and privacy concerns, other two challenges highlighted in empirical findings relate to the need of having capabilities to understand data-insights and the requirement of investments in technologies and skilled people.

As far as the former, experts A and D perceive that if decision-makers are not able to understand insights from data, their decisions might result to be wrong. This seems to reflect what The Economist (2018) describes as the lack of data literacy. Moreover, that could also be connected with the challenge arising from lack of communication skills of analytical personnel reported by respondent M from Telia Carrier and the risk of misunderstanding within enterprises, especially if big, reported by expert A and confirmed by Ericsson's representatives.

As far as the latter, respondents from TalkPool AB, GothNet and Telia Carrier perceive investments in technologies and hiring skilled people as challenging since they represent source of cost for them. However, for the sake of clarity, it is important to keep in mind the already explained differences concerning these three companies. On the contrary, Ericsson's representatives do not directly emphasize it, probably because they have already overcome this issue.

Finally, as will be further addressed in paragraph 5.3, Telia Carrier and GothNet respondents perceive the process of changing to become data-driven threatening from two slightly different perspectives. The former refers to the need of time to pursue the objective while the second remarks the presence of some resistance to change.

5.2.4 Future expectations on data-drivenness

In the literature review, the author did not focus on discovering future trends of data-drivenness development. However, in order to strengthen the answer to the main research question, the researcher felt relevant to explore how companies forecast the future of data-drivenness. Thus, empirical findings about it are analyzed by comparing them across each other, considering both experts and companies' respondents. In fact, given that companies pertain to the same sector, even though doing different activities, the future expectations almost correspond among each other, but with some elements of difference which appear to be intriguing.

From a general view point, experts A believes that the entire society will be affected by the creation of more data and data-drivenness will be the prerequisite for companies to survive. Similarly, expert D from IBM perceives that in EU enterprises will become fully data-driven in order to be able to compete and experts from Meltwater believe that enterprises will increasingly rely on external sources of data to inform their decisions. Despite this optimistic vision, they also agree on projecting the presence of stricter privacy legislations that companies will need to comply with. Furthermore, experts do not explicitly distinguish between strategic or operational decisions that, instead, is pointed out by some case companies as far as their future is concerned. For instance, respondent L perceives that in GothNet data-drivenness will mostly affect operational decisions that will be automated while respondent E from TalkPool AB expects automated decisions also in the field of marketing and sales. Despite specific case differences, all case companies agree on forecasting their future as being characterized by increasing level of data-drivenness.

A commonly agreed element by both experts and case companies' respondents is that more technologies will be developed that will enable enterprises to better exploit big data. In particular, the centrality of AI and prescriptive analytics have been highlighted.
The former is perceived to be the key for supporting decision-makers in understanding how to use data-insights for strategic decisions and for automating operational ones. In this light, expert B from Meltwater projects that in 15 years 90% of decision-makers will use less intuition and more facts and expert A forecasts that employees at different positions will be able to take decisions based on evidence from data. An interesting aspect is that while respondent E from TalkPool AB perceives that within 30 years AI will replace human decision-makers' role, respondent M from Telia Carrier believes that interaction between humans and technologies will remain crucial.
The latter is mainly addressed by expert C and respondent H from Ericsson who believe that prescriptive analytics will be used in order to guide strategic decision-making process when more options are present. In line with this, interviewee F from TalkPool AB, suggests that this kind of analytics will be largely used by big companies that have more data from different sources to combine. Finally, this expectation on the use of prescriptive analytics corresponds with the theoretical definition provided by Blackburn, et al., (2017).

Summing up the analysis carried out for category (2) Data-drivenness and taking into account the sub-categories examined, it is inferable that this section contains the majority of aspects useful to answer the main research question. In this perspective, the following summary tables contain the most relevant factors contributing to explore how companies are dealing with data-drivenness as explained in purpose and research question (paragraph 1.3). Indeed, they shade the light on comparing how enterprises define the concept and which are the elements typifying it; the main opportunities from being data-driven as well as the critical challenges; ending with future expectations.

As for category (1) of analysis, it should be remarked that in tables the absence of many disagreements (X) across findings might be explained by the fact that case companies are all B2B pertaining to the same sector and that the presence of agreement (✓) does not necessarily mean that all companies are acting in the same way, as detailly explained during the analysis. Furthermore, it might be that theory highlights something expressed also by respondents but with differences not explicable in a table.

Table 7: Summary of data analysis (category 2)

	Data-drivenness								
	Defining data-drivenness						**Opportunities**		
	Data-driven decisions	**Operational/ strategic decisions**	**Data sources combination**	**Collaboration /sharing data**	**Data-driven culture**	**Technologies & human skills**	**Better, precise, efficient decisions**	**Follow market trends & needs**	**Competitive advantage**
Senior manager innovation and digital services (respondent A)	✓	-/-	✓	-/✓	✓	-	✓	✓	-
Meltwater representatives (respondents B/C)	✓	-/-	✓	✓/-	✓	-	✓	✓	✓
Technology executive IBM (respondent D)	✓	✓/✓	-	-/✓	✓	✓	✓	✓	-
TalkPool AB (respondents E/F)	✓	-/-	-	-/-	✓	-	✓	✓	-
Ericsson (respondents G/H)	✓	✓/✓	✓	✓/✓	✓	✓	✓	✓	-
GothNet (respondents I/L)	✓	✓/-	✓	✓/✓	✓	✓	✓	✓	✓
Telia Carrier (respondent M)	✓	✓/✓	✓	✓/✓	✓	✓	✓	✓	✓
Theory	✓	-	✓	✓/✓	✓	✓	✓	✓	✓

Legend: the table shows the main paths upon which respondents and theory either agree (✓), disagree (X) or did not explicitly utter (-)[12].

[12] If the title in the table has a /, then the symbols in the respective cell will be two. The former referring to the words before the slash and the second referring to the ones after.

Table 8: Summary of data analysis (category 2 cont.)

	Data-drivenness					
	Challenges				Future expectations	
	Data-quality & reliability	**Privacy**	**Capabilities to get & share data insights**	**Investments in tools & people**	**More data-drivenness**	**Technological developments**
Senior manager innovation and digital services (respondent A)	✓	✓	✓	-	✓	-
Meltwater representatives (respondents B/C)	✓	✓	-	-	-	✓
Technology executive IBM (respondent D)	✓	✓	✓	-	✓	✓
TalkPool AB (respondents E/F)	✓	-	-	✓	✓	✓
Ericsson (respondents G/H)	✓	-	✓	-	✓	✓
GothNet (respondents I/L)	✓	-	-	✓	✓	-
Telia Carrier (respondent M)	-	-	✓	✓	✓	✓
Theory	✓	✓	✓	✓	-	-

Legend: the table shows the main paths upon which respondents and theory either agree (✓), disagree (X) or did not explicitly utter (-)[13].

[13] If the title in the table has a /, then the symbols in the respective cell will be two. The former referring to the words before the slash and the second referring to the ones after.

5.3 Organizational change

5.3.1 Defining organizational change

As explained in the literature review (paragraph 2.4), the author felt relevant to analyze theory about organizational change since facing digitalization, embracing big data and BDA and establishing data-driven culture were considered to be challenging elements for companies willing to become data-driven. However, given a lack of specific academic literature on organizational change in the light of data-drivenness, in chapter 2 the author carried out some personal speculations about it, starting from selected literature on change that seemed to be appropriate in the context of this research. Thus, in order to properly answer the sub-research question ("*How are these companies changing to become data-driven?*"), the analysis of this category compares experts, case companies' respondents and researcher's speculations and selection of change theory relevant for this study.

To begin with, as conjectured in the literature review, according to the majority of respondents, companies faced the need to adapt to digital technologies and in particular to BDA as reaction to what competitors where doing. In detail, in line with the practical view of Boss (2016) and the theoretical perspectives provided by Jones (2013b), Chakravarthy (1982) and the adaptation theory of Hannah and Freeman (1984), both Ericsson representatives and respondent I from GothNet explain that adaptation to digitalization and adoption of big data, BDA and related technologies were required due to pressure from the external environment in order to remain competitive in the market. Diversely, respondent M from Telia Carrier considers changes in the external environment not as pressures but as influences that the company received and decided to tackle.

Moreover, conforming to author's speculations, empirical findings reveal that the adoption of BDA is considered at the foundation of the process of becoming data-driven, since it entails the capability of making sense of data. As a matter of fact, all respondents believe that changes to adopt BDA involve investments in skilled employees such as data scientists and data analysts and in technological tools, as suggested by Mirvis, et al (1991) in relation to the introduction of a new technology. In fact, such investments result in establishment of new roles, creation of new jobs and substitution of others and new working styles and procedures. These changes are commonly agreed but each case company is dealing with them relatively to its specific characteristics, for instance in terms of size and profits. In this sense, the investments that Ericsson is doing are probably more significant than the ones of Telia Carrier, that in turn are higher than the ones of GothNet. For obvious reasons, TalkPool AB' representatives provide only their projections about the adaptation process that the company might face, and they also add that given the its nature being a technology provider, changes will probably be less shocking than in other companies.

Nevertheless, becoming data-driven seems to be not only about investing in skills and technologies that constitute its basis. Needless to say, respondent M from Telia Carrier describes the process as "*evolutionary and time requiring",* and interviewee H describes it as a "*change management task".* In particular, experts A and D, respondents from Ericsson, GothNet and Telia Carrier observe the presence of another element subject to change in this process: the culture or mindset of companies. However, in this regard, interviewees display two different perspectives.

On one side, some seem to confirm the adaptation model of Kitchell (1995), in considering corporate culture the enabler of the adaptation process to adopt new technologies like BDA and becoming data-driven. For instance, expert D from IBM states that an "*open-mindset"* allows companies to easily adapt to modifications required by the external environment while GothNet' interviewees believe that change is a matter of transforming corporate mindset to let it be open and aware of data value. In fact, respondent L from that company perceives that they are less data-driven than how they could be due to the fact that the right mindset is not yet in place.

On the other side, according to others, modification in organizational mindset is the results of changes from embracing data-drivenness. In this perspective, respondents from TalkPool AB estimate that in the "*learning process"* of becoming data-driven the mindset will convert in one where reliance on intuition will progressively decrease. Similarly, both Ericsson' and Telia Carrier' representatives believe that in their enterprises culture is changing as a consequence of modifications in working environment and style.

Moreover, as far as modifications in mindset and intuition value are concerned, expert A believes that the HiPPO concept explained by McAfee and Brynjolfsson (2012) is likely to change as decision-makers at different levels within the organization will be entitled to take decisions supported by evidence from data.

Additionally, an aspect addressed during all the interviews concerns the role of top-management in this changing process. Indeed, in agreement with Halaweh and Massry (2015) and Mikalef, et al. (2017), all respondents stress the importance played by the top-management support since it is entitled of defining vision to follow and investments to undertake. However, except for TalkPool AB respondents, the rest also admits that the process of change starts thanks to a push from the bottom of the organizations where employees feel the need to embrace data-drivenness. As a matter of fact, as illustrated by expert C from Meltwater top-management is often skeptical compared to lower level employees. Probably, the reason why respondent F, the CEO of TalkPool AB, does not perceive a net distinction between a bottom-up and top-down approach, is that the firm is so small and flat that a clear difference among levels in the organization does not exist.

Lastly, it appears relevant to compare some opinions that respondents gave on the impact that company size has in the journey to become data-driven. In effect, according to expert C from Meltwater small and medium companies more easily adapt to modifications whereas according to expert D from IBM, what matters more than the size is the existence of the right mindset. To provide an example, the former perspective seems to be confirmed by what Ericsson is experiencing, given that it is a big enterprise with 12000 employees only in Sweden. In fact, its representatives explain that data-drivenness is impacting departments and functions to different degrees and that the process of change to become completely data-driven is not moving at the same pace.

5.3.2 Resistance to change

In conducting preliminary researches on data-drivenness, the author found out that according to the already mentioned survey conducted by NewVantage Partners (2018), resistance to change was perceived to be the main cause of lack of successful adoption of big data and BDA within studied companies. However, as for organizational change, the researcher noticed also a scarcity of literature about it in the light of data-drivenness. For this reason and in order to strengthen the answer to the sub question, in chapter 2 (section 2.4.2) the author carried out some speculations about it, starting from academic literature on resistance to change, trying to imagine how it could be related to the context of this research and collecting respondents' perspectives about it. Thus, the analysis relates author's speculations based on general theory about resistance to change with empirical findings.

At first, agreeing with Jones (2013b), expert A notes that resistance is part of change in many enterprises. In effect, Ericsson, GothNet and Telia Carrier perceive that in their company the process of embracing BDA and becoming data-driven is being characterized by some resistance to change. From another perspective, expert D from IBM remarks that it depends on age, innovation and changing culture of companies as well as on the industry in which they operate, meaning that if it is highly conservative and stable, change is not on the order of business. This argument is taken by TalkPool AB' respondents who perceive that their company is characterized by *entrepreneurial spirit*, so they are open to change. This could also be the result of the company being a tech company, entered in the Swedish market few years ago and with very few employees.

Overall, empirical findings seem to confirm selected theory in literature review, showing the presence of two main reasons behind resistance to change.

Firstly, the willingness not to losing something valuable cited by Kotter and Schlesinger (1979), could be explained by the fear of losing the job, the decrease of intuition and the loss of power expressed by respondents. In particular, according to interviewees G from Ericsson, L from GothNet and M from Telia, the adoption of new technologies that enables automation could be perceived as menace by employees that dread to be replaced losing their job. In addition, respondents H from Ericsson, L from GothNet and M from Telia Carrier, glimpse the reduction of intuition and power resulting from data-drivenness as threatening.

Secondly, in accordance with Lawrence (1969) who outlined the presence of a technical aspect causing resistance related to modifications in the way of working due to adoption of new technologies and with the low level of tolerance highlighted by Kotter and Schlesinger (1979), the fact that becoming data-driven usually entails the creation of new working styles, is considered by respondents cause of resistance. In fact, as suggested by experts A, B and C, employees need to adapt the way of performing activities and processes. This aspect is perceived also by Ericsson, GothNet and Telia Carrier that commonly affirm the creation of new jobs or of new procedures requiring new skills.

Finally, in the literature review it was reported that Lawrence (1969) underlines the presence of another element causing resistance to change: the social aspect. It refers to the fear caused by changes in relationships in the organization resulting from various kind of changes. This has not been specifically addressed by respondents, but it could originate from the variation in roles within organizations.

Summing up the analysis presented for category (3) Organizational change, it can be said that in order to become data-driven enterprises encompass some tangible and intangible modifications, often facing some resistance to change. To be noticed that, as explained during the analysis carried out in the previous pages, even if change patterns are similar, specific characteristics of companies make their realization diverse across cases.

The table below recaps the main aspects addressed and used to answer the sub research question.

For the sake of clarity, it should be recalled that theory on organizational change does not directly tie it to data-drivenness. Hence, as highlighted by footnotes below the table, the agreement signs (✓) on theory mostly refers to general theory on organizational change that the author reasoned upon in the context of this study.

Table 9: Summary of data analysis (category 3)

	Organizational Change						
	Defining organizational change				**Resistance to change**		
	Adaptation to digitalization, big data and BDA reaction to external environment	**Tangible modifications**	**Culture enabler of adaptation**	**Top management support / bottom-up process**	**Change characterized by resistance**	**Fear of losing job/power**	**Fear of new working styles**
Senior manager innovation and digital services (respondent A)	✓	✓	✓	✓/✓	✓	-/-	✓
Meltwater representatives (respondents B/C)	✓	-	-	-/✓	✓	-/-	✓
Technology executive IBM (respondent D)	✓	✓	✓	✓/✓	X[14]	-/-	-
TalkPool AB (respondents E/F)	-	-	X	✓/-	X	-/-	-
Ericsson (respondents G/H)	✓	✓	X	✓/✓	✓	✓/-	✓
GothNet (respondents I/L)	✓	✓	✓	✓/✓	✓	✓/✓	✓
Telia Carrier (respondent M)	✓	✓	X	✓/X	✓	✓/✓	✓
Theory	✓	-	✓[15]	✓/-	✓[16]	✓/✓[17]	✓[18]

Legend: the table shows the main paths upon which respondents and theory either agree (✓), disagree (X) or did not explicitly utter (-)[19].

[14] The expert believes that resistance depends on company age, innovation & change culture
[15] General theory on resistance to change, not specifically in process to become data-driven
[16] See footnote 15
[17] See footnote 15
[18] See footnote 15
[19] If the title in the table has a /, then the symbols in the respective cell will be two. The former referring to the words before the slash and the second referring to the ones after.

6. Conclusions and future research

This final chapter aims at presenting conclusions of the study conducted by answering the research question and the sub-question. At the end of section 6.1 a figure summarizing the essential reasoning followed along conclusions is provided. Furthermore, the author remarks some personal comments concerning case companies. Finally, suggestions for future research are presented.

6.1 Conclusions

As introduced at the beginning of this research (section 1.1), companies are currently operating in the digitalization era characterized by the application of digital technologies in many aspects of business. The main outcome is the creation of increasingly larger amounts of data that can be collected and handled with technologies such BDA. Given the context, the author felt plausible to believe that digitalization, and in particular big data and BDA considered as new technologies, act as an external pressure for companies that need to adapt to these novelties to survive and remain competitive in the market. In fact, companies can create value from big data by extracting relevant insights that guide better decisions. Thus, the outcome is that many companies are working for becoming data-driven.

Given this summary of the background and considering the more detailed explanation provided in the introduction (section 1.2), a preliminary analysis let the author focusing on Swedish-based B2B companies operating in the telecommunication sector. The aim was to qualitatively explore how they are dealing with data-drivenness with the overall goal of academically contributing to existing studies on this topic. In particular, the purpose of the research was to seek how case companies **define** data-drivenness, the **main elements** characterizing it, **opportunities** and **challenges**, their **future expectations** and the implied **organizational changes** if present.

Thereby, research question and sub-research question are reported again:

"How are B2B companies in the telecommunication sector dealing with data-drivenness?"

"How are these companies changing to become data-driven?"

In order to answer these questions, the author will now present a comprehensive conclusion to the research.

In the light of the research it seems reasonable to state that B2B companies within the telecommunication sector are living into some sort of loop where they are the building blocks of the creation and transmission of data and, at the same time, they seek to benefit from it being or working for becoming data-driven. As a matter of fact, case companies are aware of what data-drivenness is and they **define** a data-driven enterprise as one able to convert data into insights used to inform

decisions, where data is considered an asset and where decision-makers' knowledge and expertise is coupled with evidence from data.
From these definitions collected through empirical collection and deeply analyzed in the light of the literature review conducted by the author, it is inferable that big data and BDA are at the foundation of data-drivenness. Notwithstanding the absence of a threshold beyond which the amount of data collected by companies is defined as "big", the ability to combine internal and external sources of information is deemed crucial to be data-driven. In fact, it enables to extract valuable insights with BDA to inform decisions. What is noticeable is that not only size and activities of companies affect the amount of data collected but also the typologies of data sources to combine. In the context of this thesis, Ericsson and Telia Carrier combine internal with external data from market trends such as social media and editorials analysis while GothNet connects internal data with external geographical locations.

Having stated that case companies mostly agree on how they define a data-driven enterprise, the reader might be wrongly conveyed to deduce that all B2B enterprises in telecommunication sector included in this research are implementing data-drivenness identically. However, the study showed that data-drivenness is implemented differently and that it might involves strategic and/or operational decisions depending of company' willingness and specific characteristics. In detail, TalkPool AB is not data-driven since it is not collecting and analyzing data for its own purposes at the moment; GothNet is driven by data in automated operational decisions; Ericsson and Telia Carrier are implementing data-drivenness at higher pace being data-driven in both strategic and operational decisions pertaining many different activities.

After having outlined how companies define data-drivenness in general and in their specific contexts, the consequent step for answering the first research question is to outline which are the **main elements** that characterize them in being data-driven. Before presenting those, it appears necessary to recall the upper-explained distinction in terms of data-drivenness implementation because for obvious reasons, TalkPool AB did not provide opinion about this for its specific case.
The major features typifying data-drivenness within selected companies resulted to be coherent with theoretical findings that the author presented in three categories: tangible resources, intangible resources and human skills[20]. However, according to the researcher the remarkable aspect that differentiates reality from theory is that in theory everything seems to be "bad of roses" while in reality all emerges to be extremely interconnected and often complex, as presented below.

[20] Section 2.3.1.1 and figure 3

With regard to the fact that big data, BDA and related technologies constitute the bedrock of data-drivenness, the presence of human skills appears to go hand in hand. Indeed, having infrastructure and analytical technologies without having skilled employees capable of exploiting that tools and make sense of insights from data, would be pointless. In this logic, studied enterprises started to hire talented personnel in this field such as analytics and data-scientists even though to different extents as explained above (section 5.2.1).

Moreover, human skills resemble to be essential for the existence of collaboration within the organization, another element of data-driven companies. Precisely, it entails that diverse functions and departments collaborate by exchanging relevant information and, essentially, the analytical part of company jointly works with the decision-making part. This is made possible thanks to the capability of the former to communicate results and insights to the latter as well as to the possibility to access and share data across departments. In particular, sharing of data is another main element outlined by case companies. However, both collaboration and data sharing occur with some differences as illustrated during the analysis (section 5.2.1).

Lastly, the mindset of such enterprises is theoretically defined under the name "data-driven culture". However, culture is an extremely broad topic and in reality, is manifested in the form of many different facets since it refers to the way in which people within the organization consider data. What is more, just because humans are involved, having a unique data-driven culture within organization is perceived to be complex and not yet in place in case companies. On the whole, the mindset of data-driven enterprises values data as other assets, trusts data-related aspects and insights and embeds them into daily activities and decisions. Furthermore, intuition is deemed to be integral part of organizations' culture since being data-driven entails a reduction of the reliance on solely intuition to bring decisions thanks to the combination with insights from data, apt to prove or disprove decision-makers' gut feeling.

Although case companies are implementing data-drivenness or considering the possibility of doing so, as for TalkPool AB, some **critical challenges** have been outlined throughout the research and it is believable that these prevent them from being fully data-driven. In particular, not by chance the majority of issues highlighted relate to elements constituting data-drivenness. Firstly, the need to check data quality with validation due to risk of manipulation. Secondly, the lack of capabilities to understand data threats the realization of the above-explained collaboration within the organization, leading to misunderstandings, scarcity of communication and consequent mistaken or inaccurate decisions. Thirdly, hiring skilled employees and acquiring advanced technologies to perform analytics often requires relatively huge investments representing a source of cost for companies. Lastly, an overall challenge that the researcher glimpses relates to the process of change undertaken by companies to become data-driven.

As a matter of fact, **organizational change** emerged to be crucial for case companies in order to react to technological modifications in their surroundings. In particular, in response to competitors' influence and pressure from the external environment, enterprises might decide to adopt big data and BDA, starting the process of becoming data-driven. This decision, most likely, lies in various **opportunities** that companies foresee from data-drivenness. In fact, experts and case companies, in accordance with theory, believe that data-driven decisions are better, more accurate and precise. In detail practice, in terms of strategic decisions they can improve forecasts and planning, targeting and business development. As far as operational ones, the general opportunity related to increase efficiency with automation. Moreover, thanks to insights from data, enterprises can discover unknown factors, new innovation avenues and follow customers' needs, therefore improving their competitive position in the market. Thus, taking into account the clarifications made above, one can believe that TalkPool AB projects to become data-driven in the light of these opportunities while the rest of case companies has previously evaluated them having already started the process toward full data-drivenness.

As explained in the very beginning of this study, organizational change theories do not directly tie it to data-drivenness, hence the author decided to include the sub-research question that will now be answered.

Data-drivenness is not only a matter of introducing a new technology and the change at the heart of the process encompasses both tangible and intangible modifications mainly linked to its characterizing elements.

On one side, in order to become data-driven companies ought to invest in skilled employees and new technologies in data analysis field. These consequently cause the creation of new jobs or substitution of others, the settlement of new roles and the introduction of new working styles and rules. To provide a more practical example, the implementation of the above explained collaboration within organizations might be one of the tangible changes in the light of data-drivenness.

On the other side, companies face changes in the culture and mindset. In detail, according to some experts and to GothNet, culture is the enabler of this changing process. Diversely, other case companies perceive modifications in the mindset as the outcome of changes resulting from data-

drivenness encompassment. Moreover, the majority of case companies believes that, despite the fact that this journey should be guided and supported by the top-management, the push for it arises from the bottom level employees.
Finally, a critical issue experienced during the process of change is resistance toward it. The roots of it could be seen in the fear of losing or changing job, fear of losing power, in required adaptation to new procedures and to acquire or develop new skills.

Lastly, it seems reasonable to state that data-drivenness is a hot topic given the continuous creation of increasingly larger amount of data at companies' disposal. Thus, respondents share their **future expectations** on it. Experts believe that digitalization will increasingly affect the entire society. Hence, data-drivenness will probably be the prerequisite for companies to survive and remain competitive in the market by exploiting all insights at their disposition, especially from external sources. Though, they project the drawback related to the emanation of strict legislations to monitor data-usage and protect customers. Furthermore, case companies envision the future of data-drivenness as being characterized by technological developments such as AI and prescriptive analytics which will incrementally support decision-makers by guiding decisions.

To sum up the conclusions, it seems reasonable to state that B2B companies within the telecommunication sector are living into some sort of loop where they are the building blocks of the creation and transmission of data and, at the same time, they seek to benefit from it being or working for becoming data-driven.
In fact, the case companies are aware of what a data-driven enterprise is, and which are the elements characterizing it. However, data-drivenness turns out to be implemented to different extents within case companies, mainly because of their diverse size and key peculiarities. Moreover, there are some critical challenges preventing companies precluding full data-drivenness. Among these, the complex bottom up process of change undertaken to become data-driven that often encounters some resistance. De facto, in order to evolve into a data-driven enterprise companies encompass both tangible and intangible modifications which are mainly linked to data-drivenness elements implementation such as the implementation of new roles, different procedures and data-driven culture. Hence, it is plausible to believe that companies decide to start the journey toward data-drivenness in the light of opportunities connected to it such as the possibility of bringing more accurate decisions and following market trends improving their competitive position.
Finally, the research discloses that data-drivenness is a hot topic and likely to be the future prerequisite for companies to survive in an increasing digitalized and evolving world.

The following summary figure aims at providing the reader with a graphical representation of the flow followed by the researcher in comprehensively answering the research questions.

Figure 5: Summary of conclusions

B2B companies within the telecommunication sector in a "loop":
building blocks of digital revolution for creation and transmission of data
& seek to benefit from it with data-drivenness

↓

Awareness of data-drivenness and its characterizing elements:
big data & BDA, human skills, collaboration, data-sharing, mindset
BUT implementation at different degrees

↓

Critical challenges preventing full data-drivenness:
data quality, lack of capabilities, investments in people & tools,
complex change to become data-driven

↓

Bottom up change process with tangible & intangible modifications linked to data-drivenness elements implementation:
skilled employees and technologies, creation of new roles & procedures and data-driven culture

↓

Becoming data-driven to catch opportunities:
better decisions, innovation, follow market trends, competitiveness

↓

Data-drivenness prerequisite to compete BUT more regulations
+ technological developments for analysis

6.2 Final remarks on case companies

This paragraph attempts to present to the reader some author's personal considerations on case companies emerged along the research conducted.

As deeply explained in the course of data analysis and conclusions, data-drivenness resulted to be implemented at different degrees by case companies. At the beginning of the study, the author intentionally decided to select B2B enterprises performing different activities in the telecommunication sector, with different size and with presence in Sweden since different moments in time. Recalling the differences outlined during the explanation of case companies selection (paragraph 3.2) the researcher initial hunch was that company size and newness to the Swedish market could be the determining factors impacting the potential difference in the way companies were dealing with data-drivenness.

Now that the study is drawing to a close, the author realized that the former has a great impact while the latter's importance is subordinated to other elements. As a matter of fact, companies' peculiar characteristics ended up playing a crucial role, especially in the change process underpinning data-drivenness realization.

The extreme small size of TalkPool AB and the fact that it was established in the big data era would lead it to an easy-going change. However, its little number of clients and business activities creates a barrier related to the very first decision of undertaking the process toward data-drivenness. Indeed, notwithstanding the general opportunities foreseen, TalkPool AB is probably not perceiving them in its own context, hence they appear not to be worth it. In particular, at the moment the company presumably has low variety of data sources to combine as well as low investment capacity.

Ericsson and Telia Carrier, belonging to the category of large companies[21], are highly investing in technologies and human skills with data-drivenness target. However, exactly for their size, resulting tangible and intangible modifications might be hard to manage. Differently from TalkPool AB, they have probably undertaken the journey as they glimpse real and applicable opportunities arising for data-drivenness. Just to recall, their specific characteristics such as the fact that they perform multiple activities with a global presence enable them to have access to various kind of internal and external data sources that, combined, open up a vast array of opportunities.

Lastly, being GothNet a municipal company, it believably does not have complete freedom of investments. Hence, its monetary capacity of acquiring advanced technologies and hiring more skilled

[21] Large companies have 250 employees or more. (OECD,2019)

employees is limited even if their small size makes the change relatively easy. In addition, considering the target related to data-drivenness achievement, things differ from previous cases. The peculiar fact that GothNet is municipal with a presence in a limited region, might reduce, to some extents, the opportunities from being data-driven. De facto, it presumably has less strategic decisions to bring compared to Ericsson and Telia Carrier.

6.3 Future research

Considering that data-drivenness is likely to shape the next future of several organizations, many other studies could be performed beside the research conducted in this thesis and the existing material on this topic. Hereby, the author will suggest the future researches that appear most intriguing to be performed.

Firstly, given that data-drivenness implementation revealed not to be full within case companies, it might be interesting to perform the same study within few years or for a continuous period of time with a longitudinal design. The aim would be to explore whether and how these companies have achieved their targets concerning data-drivenness. Thus, to seek if and in what way they have overcome the critical challenges highlighted during this study.

Secondly, considering the limited time in which this study has been conducted, an additional one with a larger scope could provide more insights on how Swedish-based companies within the telecommunication sector are dealing with data-drivenness. An example could be to include B2C enterprises in the same sector with the aim of devising similarities and differences with B2B. Moreover, given that the focus was limited to Sweden, results cannot be applied to different geographical settings because results might differ across countries. Thus, a research conducted on companies within the telecommunication sector in other regions could be intriguing.

Thirdly, recalling the initial hunch of the author regarding the impact of company size and newness to a given market, a possible future study could have a quantitative nature in order to analyze to what extents and with which correlation these factors impact the way in which companies deal with data-drivenness. As a matter of fact, a quantitative study would enable the researcher to include a large sample to deduce some generalizable results.

Fourthly, taking into account the researcher's background in business and innovation management this study has been carried out from this angle. Therefore, it might be interesting to execute the study from a technical perspective in order to investigate in detail how enterprises actually manage such technologies in the context of data-drivenness. On the other side, the topic could be explored through organizational design lenses. As a matter of fact, being culture an intricated and controversial topic, a deeper investigation would be more comprehensive.

Finally, further researches on organizational and resistance to change in the context of data-drivenness should be conducted with the purpose of generate scientific literature on it. Thus, studies focused on other sectors could be carried out, considering that the topic might be diversely perceived by companies operating in different industries. A suggestion might be to compare traditional sectors with state-of-the-art ones to explore to what extent these diverge in relation to data-drivenness. Presumably, organizational changes might differ between such sectors and consequently data-drivenness might be implemented with diverse tangible and intangible modification.

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Appendix 1a

Message sent in order to contact the following respondents having FTK as intermediary:

Respondent	Title	Company
Anonymous Expert (respondent A)	Senior manager in innovation and digital services	Big Swedish corporation
Nicolas Westdahl (respondent C)	Head of Services and Support, Enterprise EMEA	Meltwater
Frode Langmoen (respondent D)	Technology executive	IBM
Boris de Bruin (respondent E)	Responsible marketing and sales	TalkPool AB
Stefan Lindgren (respondent F)	CEO CTO	TalkPool AB TalkPool Group
Jonas Wilhelmsson (respondent G)	Head of Ericsson Garage	Ericsson
Lars-Erik Lindberg (respondent H)	Innovation leader Ericsson Garage and change leader in R&D department	Ericsson
Magnus Hartmann (respondent I)	Business developer in sales and marketing department	GothNet
Per-Olof Odgren Lundh (respondent L)	IT Network specialist and system engineer	GothNet

Dear *respondent x,*
I am Giulia Di Mascio, an international student at the University of Gothenburg. I am writing my master thesis in Innovation and Industrial Management with the support of First To Know Scandinavia AB that gave me your contact. As you will probably know from them, the topic of my research is “Data-drivenness: big data and data-driven decisions” and I am seeking to explore how companies are dealing with this concept. You can find attached a short synopsis of the research to have a better idea.
I would really appreciate if you could give me one hour of your time to conduct an interview. Let me know your availability to set up a meeting.
Kind regards,
Giulia Di Mascio

Appendix 1b

Message sent in order to contact the following respondents via LinkedIn:

Respondent	Title	Company
Peter Heurling (respondent B)	Enterprise Solutions Director, EMEA	Meltwater
Per Brännström (respondent M)	Director of Business Analysis in voice trading area	Telia Carrier

Good morning,
I am Giulia Di Mascio, an international student at the University of Gothenburg and I am writing the thesis of my master in Innovation and Industrial Management. The topic of my research is Data-drivenness: big data and data-driven decisions and I am seeking to understand how companies are dealing with it. You can find attached a short synopsis of my thesis. Given your relevant position in Telia Carrier, I would really appreciate if you could give me a time slot to conduct an interview or if you could redirect me to someone within your company that would be willing to contribute to my research.
Please let me know your availability.
Kind regards,
Giulia Di Mascio

Appendix 2a

Interview guide for semi-structured interviews with experts:

Information to the respondents:
Before starting this interview, I would like to present myself and give some general information about the interview.
I am Giulia Di Mascio and I am attending a double degree program on Innovation and Industrial Management between LUISS university in Italy and Gothenburg University here. As you know, now I am writing my thesis by working with both universities and FTK that is supporting me as they probably explained you. I really appreciate the time you gave me for this interview and if you need, I can give a brief explanation of my thesis.

Nowadays companies are operating in the digitalization era, characterized by the production of progressively larger amount of data that needs to be managed and analyzed to create value. One can say that digitalization, big data and their analysis act as an external pressure for companies that need to change and/or adapt to these novelties to remain competitive in the market. The consequence is that companies are becoming more and more data-driven and this results in a decision-making process increasingly driven by data.

Thus, it seems interesting to analyze how companies are dealing with data-drivenness in their organization, by interviewing decision-makers. Moreover, to have a broader understanding of the topic, I decided to interview some key informants such as you.
I decided to focus on Telecommunication sector with B2B companies because I felt interesting to analyze companies not consumer-based.

Now just few information about the interview: it is made of two parts: questions regarding big data and BDA and questions about data-drivenness. I have prepared a set of questions that will be adjusted according to our discussion. If there are sensitive information and you don't want to answer, just tell me and if you have questions stop me at any time.
Finally, I would like to ask you if I can record this interview, it will not be disclosed to the public, but it would be really helpful for me to analyze data. Also, I will send you the transcript that you can check and agree with me.

General information:
Which is your background and your role now in your company?

Questions on big data and big data analytics:
- How would you define big data in general and with respect to digitalization?
  - Which are the dimensions/features of big data?
- How would you define big data analytics? Technologies used?
- Do you perceive that organizations have been impacted by digitalization and in particular by big data and BDA?
  - Do you perceive that they acted as an external pressure to adapt for companies?
  - How do you believe companies adapt to it?

Questions on data-drivenness:
- How would you define a data-driven company?
  - Which are according to you the main features of a data-driven company?
  - Do you think that a company can be data-driven both for strategic decisions and operational decisions such as automated processes? Which kind of data-sources for each type?
  - To what extent do you think that to be data driven companies should have accessible data across the organization?
    - Collaboration and communication within organization?
  - In your opinion, which activities/departments are more data-driven?
- Do you think that big companies and small companies deal with data-drivenness in different ways?

- Which role do you attribute to the mindset/culture of a company to be data-driven?
  - Which working environment should the company privilege?
  - Which types of analytics should companies' privilege?
  - Which is the role played by the top-management?
  - How should the decision-making process be?

- Which are the main benefits/opportunities of being/becoming data-driven?

- Which are the main challenges **o**f being/becoming data-driven
- Do you think that organizational change is necessary to become data-driven?
    - Do you think that changes in culture/ mindset are necessary to become data-driven?
    - How do you perceive the concept of resistance to change with respect to a company willing to embrace big data and BDA to become data-driven?

  - What do you think the future of data-drivenness is in general?
  - Focus on B2B respect to B2C?

Appendix 2b

Interview guide for semi-structured interviews with case companies' respondents:

Information to the respondents:
Before starting this interview, I would like to present myself and give some general information about the interview.
I am Giulia Di Mascio and I am attending a double degree program on Innovation and Industrial Management between LUISS university in Italy and Gothenburg University here. As you know, now I am writing my thesis by working with both universities and FTK that is supporting me as they probably explained you. I really appreciate the time you gave me for this interview and if you need, I can give a brief explanation of my thesis.

Nowadays companies are operating in the digitalization era, characterized by the production of progressively larger amount of data that needs to be managed and analyzed to create value. One can say that digitalization, big data and their analysis act as an external pressure for companies that need to change and/or adapt to these novelties to remain competitive in the market. The consequence is that companies are becoming more and more data-driven and this results in a decision-making process increasingly driven by data.
Thus, it seems interesting to analyze how companies are dealing with data-drivenness in their organization, by interviewing decision-makers.

Now just few information about the interview: it is made of three parts: general information about you, questions regarding big data and BDA and questions about data-drivenness. I have prepared a set of questions that will be adjusted according to our discussion. If there are sensitive information and you don't want to answer, just tell me and if you have questions stop me at any time.
Finally, I would like to ask you if I can record this interview, it will not be disclosed to the public, but it would be really helpful for me to analyze data. Also, I will send you the transcript that you can check and agree with me.

General information:

- Can you define your role as decision-maker in your company?

Questions on big data and big data analytics:

- How would you define big data and big data analytics in your company?

- How much do think that your company uses big data (and big data analytics)? (if you collect and analyze data for your purpose)?
    - o How is your company using big data? Which departments are more intensive in the usage of big data and BDA?

- How has your organization been or is being impacted by digitalization in general and in particular by big data, big data analytics?
    - o Do you perceive that they acted as external pressure to adapt for your company and how was the adaptation process?
    - o Has your organization needed to make investments in new technologies (e.g. advanced Storage systems)?
    - o Has it to hire skilled people in this field (e.g. data analysts/scientists)? Or has your organization needed to ask the support of external firms for analysis?

- Who is in charge for analyzing data in your company?
    - o Do you know to what extent are data accessible to everyone within the company?

Questions on data-drivenness:

- How would you define a data-driven company?
- How does your company use data to guide decisions?
    - o How do you use data to guide (strategic) decisions in your company? Can you give me an example?
    - o Do you believe that decision-makers relies mainly on intuition for decisions? What about you?
    - o Have you heard about HiPPOs? What do you think about it?

- Which role do you attribute to the mindset/culture of a company to be data-driven? How would you define the mindset of your company in this regard?
        - ▪ Which working environment does your company privilege?
    - o Which kind of analytics do you privilege?
    - o What do you think is the role of top management in becoming data driven?
        - ▪ Do you know if your company has established new roles at the C level such as Chief digital officer or chief data officer?

- Which are the main benefits of being/becoming data-driven?

- Which are the main challenges of being/becoming data-driven

- Do you think that organizational change is necessary to become data-driven?
    - o Do you think that changes in culture/ mindset are necessary to become data-driven?

- What do you think the future of data-drivenness is in general and in your company?